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Three essays on the impact of information and transparency in firms

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THREE ESSAYS ON THE IMPACT OF INFORMATION

AND TRANSPARENCY IN FIRMS

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ABSTRACT

This dissertation consists of three essays on the information and transparency in firms. In the first essay, we provide some of the first evidence regarding the impact of safety expenditures on moral hazard induced by increases in workers' compensation benefits. Prior studies have inferred the effect of safety incentives by testing the relation between claims frequency and benefit increases. However, these studies have not explicitly modeled the impact of actual safety expenditures. Using a proprietary dataset containing policy-level data for several thousand policies over a 13-year period we show that safety expenditures play a positive role in reducing the moral hazard response to changes in workers' compensation benefits.

In the second essay, we investigate financial strength ratings of insurance companies which have received considerable attention, with good reason due to recent insolvencies in financial institutions. Interestingly, observations of market returns around downgrades in insurer financial strength ratings (IFSR) become significantly negative, suggesting that some sophisticated investors anticipate the price reaction to downgrades which are viewed as negative news. Research argues that short sellers are informed investors as current short selling relates inversely with future returns. However, empirical results have yet to determine whether short sellers trade on private information before, say, an upcoming negative new events or whether short sellers are superior in their ability to process public information. This paper takes a step in this direction by examining short selling around IFSR by examining short-selling activity around A.M. Best ratings changes. While we find abnormal short selling prior to ratings downgrades, we

also find that an insurers' asset and liability opaqueness negatively affects the level of short selling activity prior to a financial strength ratings downgrade. We are left to conclude that while short sellers anticipate IFSR downgrades, they do not appear to be superior in their information processing ability around IFSR changes.

In the third essay, due to the advent of Enterprise Risk Management (ERM) a growing body of research related to its determinants, organization, and value-relevance has been motivated. While several recent studies test *whether* ERM benefits firms, there is an absence of studies that examine *how* ERM can generate value. Our paper provides some initial evidence on one potential source of value from an ERM program; an increase in transparency regarding the firm's risk profile. Using dispersion in analyst earnings forecasts as a proxy for transparency we find that firm-level transparency increases following the adoption of an ERM initiative. The increase in transparency is greatest for firms that are operationally and financially opaque.

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TABLE OF CONTENTS

LIST OF TABLES

ESSAY 1:

THE IMPACT OF SAFETY EXPENDITURES ON MORAL HAZARD

CHAPTER 1.1

INTRODUCTION

Prior to the passage of workers' compensation (WC) statutes in the early 1900s, recourse for work-related injuries was based on the tort system and therefore required proof of employer negligence. Employers generally prevailed in litigation; however they faced substantial risk of unpredictable losses in the event of successful worker suits. Ultimately, both employers and employees favored WC legislation that provided no-fault compensation to injured workers and substantially limited employer liability.

WC insurance, the primary mechanism for funding statutory WC disability benefits (WCB), creates incentives for workplace safety and injury prevention by tying employer premiums to their past loss history. *Ceteris paribus*, this experience rating system should decrease WC losses. However, the statutory provision of no-fault benefits for employee injuries creates incentives for greater risk taking and/or increased injury claims. An important empirical question arises: Does the safety effect of experience rating dominate the effect of employee moral hazard resulting from a no-fault benefit provision?

Using a sample of detailed policy-level underwriting, claims, and safety expenditure data for several thousand policies over the period of 1995-2007, we examine the net effect of safety expenditures on WC losses. Using this unique dataset we are able to estimate the impact of changes in safety expenditures on changes in loss costs, holding constant benefit changes. Subsequently, we show that safety expenditures play a positive role in reducing the moral hazard response to changes in WCB. Prior studies have inferred the net effect of safety incentives by estimating the relation between benefit increases and claims/injury frequency or severity (Butler and Worrall, 1991; Moore and Viscusi, 1989). However, these studies have not explicitly modeled the impact of actual safety expenditures.

We first examine changes in loss cost around changes in WCB, referred to as the *moral hazard* hypothesis. Secondly, we examine the relation of changes in safety expenditures on changes in loss costs, holding constant benefit changes, referred to as the *dominance* hypothesis. Our result in regards to the *moral hazard* hypothesis is expected. First, we find evidence of increases in loss cost around increases in WCB, *ceteris paribus*. Additionally, we find safety expenditures negatively affect loss cost, indicating the potential effectiveness of safety in reducing real injury cost. In testing the *dominance* hypothesis our results are interesting. While moral hazard is still evident in our sample, we show that safety expenditures play a positive role in reducing the moral hazard response to changes in WCB. Our findings provide some of the first evidence that safety expenditures play a positive role in reducing the moral hazard responses to changes in benefits while at the same time reducing real injury loss cost.

Empirically, the presence of moral hazard has been tested by examining the change in claims rates in response to increases in WCB. Overall, the majority of the findings support the indication that an increase in WCB leads to an increase in claims (Dionne & St Michel, 1991; Danzon & Harrington, 2001; Butler and Worrall, 1991; Meyer, Viscusi, and Durbin, 1995; Butler, Garner & Garner, 1997; Butler, Garner & Garner, 1998; Butler, 1994; Ruser, 1991). Our univariate tests indicate that the greater the increase in WCB the larger the change in loss cost. This result is consistent with the *moral hazard* hypothesis and previous literature that as benefits increase moral hazard is one resulting outcome.

In our multivariate tests we find an increase in loss cost around changes in WCB, *ceteris paribus*. Our results are consistent with moral hazard with existing benefit changes (Dionne & St Michel, 1991; Danzon & Harrington, 2001; Butler and Worrall, 1991; Meyer et al., 1995; Butler, et al., 1997; Butler et al., 1998; Butler, 1994; Ruser, 1991). In addition, we examine the relation between safety expenditures and loss cost holding WCB constant. Our results indicate a negative relationship, suggesting safety expenditures play a positive role in reducing the moral hazard responses to changes in benefits while at the same time reducing real injury loss cost. These findings are relevant in the WC literature as others (Butler and Worrall, 1991), have indicated that moral hazard dominates the safety incentive for the employer. Our results provide initial evidence that while moral hazard exists, safety expenditures reduce the dominating moral hazard response observed around WC benefit changes.

We further extend our analysis by examining the relation between safety expenditures and loss cost holding WCB constant, in a sub sample of claims related to hard to diagnose injuries, and claims of a lengthened duration. Butler et al. (1997) reports the distribution of WC claims has exhibited a shift towards soft tissue injuries such as sprains, strains, and low back claims, and that nearly 30% of the increase in soft tissue related claims can be explained by moral hazard (Butler, et al., 1997; Butler et al., 1998). Further, a number of studies show that WC claim duration is affected by the monetary incentives and socioeconomic characteristics (Butler & Worrall, 1985, Fenn, 1981; Meyer et al., 1995, Fenn, 1981). Meyers et al. (1995) and Fenn (1981) show time out of work increased based on the generosity or level of WCB available. Similar to our complete sample, we find evidence of moral hazard when conditioning on hard to diagnose injuries and the duration of claims development. More importantly, we find when conditioning on claims characteristics synonymous with moral hazard, we again find a negative relationship, suggesting safety expenditures play a positive role in reducing the moral hazard responses to changes in benefits while at the same time reducing real injury loss cost.

The next section reviews related prior literature. The following section develops our hypotheses, and sample and data are introduced in the subsequent section. The next two sections present our empirical methodology and discuss our results. The final section concludes.

CHAPTER 1.2

PRIOR LITERATURE

Workers' compensation provides benefits to employees who are injured at work or sustain a work-related illness/disease. These benefits include medical expenses for work-related conditions, payments that partially replace lost income and survivor benefits when a fatality occurs. According to the National Safety Council, between 1972 and 1992, US employer costs for providing WC increased from $6 billion to $61 billion, a yearly growth rate of 12.5%; then reaching $64 billion in 2001. In 2006, the economic impact of workplace injuries was estimated to be $164.7 billion (National Safety Council, 2007), with WC cost of $12.58 per $100 of covered wages, total cash benefits to injured workers and medical payments for their health care were $54.7 billion, and costs to employers were $87.6 billion (National Academy of Social Insurance, 2007).

Prior to the inception of WC legislation, there was a single recourse for an injured worker's work-related injury. This was to bring a legal suit against the employer and prove that the employer's negligence caused the injury. When the tort system was the only option for settlement, a majority of the time the workers did not recover damages and experienced delays in receiving compensation for their work related injuries. However, while employers usually were successful in a legal defense, there was a significant risk for large losses if the worker prevailed with the suit. Overtime, both employers and workers were in favor of WC legislation which ensured that a worker who sustained a work related injury/illness or disease arising out of and in the course of employment would receive benefits, regardless of who was at fault. In order to do so, the employer's liability was limited, providing the exclusive remedy model where the worker accepts WCB as payment in full and gives up the right to sue.

While the movement for the adoption of WC was to replace employers' tort liability with a no-fault system, the systems structure through the use of experience rating and federal statues imposes incentives for safety. Workers compensation is expected to encourage employers to provide improved workplace safety because each employer would take on the costs of its workers injuries more so than under tort liability. The foundation for this approach is that risk-based premiums are more reasonable and also promote greater system effectiveness by convincing employers to internalize more of the costs associated with their risk level. In theory, this should encourage employers to optimize expenditures on safety and the control of compensation costs; such that the cost of injuries would be included in the employer's business costs, and employers would be motivated to reduce premium costs by placing an emphasis on the safety and improving working conditions.

Although the WC system resulted in consistent and predictable benefits without the employee/employer relationship enduring a legal process; the expectation of enhanced safety did not take into account factors that would weaken safety. The most widely examined of these factors is moral hazard. Due in part that wage-replacement benefits compensate employees for not working, there is an inherent behavioral incentive to amplify the severity of existing injuries, time away from work due to injury, and/or misrepresenting where the injury occurred (i.e. work or away from work). This misrepresentation of risk is termed "moral hazard" and comes from the information asymmetries between employer and employee.

Dionne & St Michel (1991) presented early work looking at moral hazard in the WC system and suggested two types of moral hazard. The first type is related to self-prevention activities affecting probabilities of accidents. The second type relates to the insured activities whenever the accident occurs. Their results indicated that moral hazard was present due to the outcomes that the length of the recovery period was associated with an increase in insurance coverage for injuries which are difficult to diagnose. Several studies of the moral hazard effects have confirmed that higher WCB tend to increase the frequency and duration of claims (Danzon & Harrington, 2001; Butler and Worrall, 1991; Chelius, 1977; Cheluis and Kavanaugh, 1988).

Butler and Worrall (1991) summarizes the ways in which moral hazard develops, suggesting when indemnity benefits increase, workers may engage in more risks, since the cost of lost income is reduced. Additionally, since the increase in benefits results in higher premiums, employers may initiate risk control measures. The combination of the effects is referred as "risk bearing" moral hazard. Butler and Worrall (1991) introduce a second type of moral hazard which occurs when workers reports claims for a level of injury for which the worker would not have reported a claim, whereas the employers may respond with increased monitoring claims. The combination of the worker and employers response is termed "claims bearing" moral hazard. Butler & Worrall (1991) investigate the two types of moral hazard and suggest that loss growth largely reflects increased claims reporting rather than increased employer or employee risk-taking behavior. Overall, the majority of the findings lend support that an increase in benefits leads to an increase in claims (Danzon & Harrington, 2001; Butler and Worrall, 1985; Meyer et al., 1995; Butler et al., 1997; Butler et al., 1998; Butler, 1994; Ruser, 1991).

More recent moral hazard literature has investigated claims behavior related to hard to diagnose injuries (i.e. soft tissue injuries) (Butler, Durbin, &. Helvacian, 1996). These types of injuries lend themselves well to an increased proportion of moral hazard initiated claims. Butler et al. (1996) reports the distribution of workers' compensation claims has exhibited a shift towards soft tissue injuries such as sprains, strains, and low back claims. Furthermore, the authors report that nearly 30% of the increase in soft tissue related claims can be explained by moral hazard. These findings are consistent with Butler (1994) who shows increases in both the frequency and severity of insurance claims as the wage replacement rate increased and as the waiting period decreased. These findings are supporting early work by Ruser (1991) who suggested higher benefits are found generally to increase lost-workday cases. Overall, results consistently indicate an increase in WCB resulted in an increase in claims.

In a similar stream of literature focusing on claims characteristics, a number of studies show that workers compensation claim duration is affected by the monetary incentives and socioeconomic characteristics (Butler & Worrall, 1991, Fenn, 1981; Meyer et al., 1995; Butler, Baldwin, & Johnson, 2001). Meyer et al (1995) investigated the effect of workers' compensation on time out of work around increases in maximum weekly benefits. In their sample, benefit amount for high-earnings individual’s increases by approximately 50 percent, while low-earnings individuals did not experience a change in their incentives. The findings indicated time out of work increased for those eligible for the higher benefits and remained unchanged for those whose benefits were constant. Fenn (1981) focuses on the duration of individual sickness absence using British survey data of illness or injury victims. He found that as the relative generosity of sick pay increased, there was a disincentive effect in that the duration of illness lengthened. Butler et al. (2001) follow and examined workers compensation claim duration for workers with serious low-back injuries, reporting elapsed claim duration vary significantly with employee characteristics and economic incentive to return to work.

There are a few findings that differ from the consensus, by showing when the risk measure more accurately captures the severity of accidents; benefit increases have a negative effect on risk levels for more severe risks. Chelius (1976) found that the introduction of WC resulted in a decrease in fatality rates over the period 1900-1940. Chelius (1982) examined the impact of workers' compensation benefits on the allocation of resources to injury prevention. His findings suggests that higher compensation benefits are associated with lower severity rates of injury, suggesting that higher benefits induce employers to spend more on the prevention of serious injuries. Moore and Viscusi (1989) suggested that the most severe accidents should reflect very little moral hazard, since for example traumatic injuries or deaths cannot be falsely claimed. This is to say that the value a worker implicitly attaches to their life suggest that workers are not willing to substitute fatality benefits for their own life. Therefore, if workers' compensation provides any safety incentives to firms, these will be reflected most strongly in the fatality rate data. Moore and Viscusi (1989) reported a dramatic safety effect without a moral hazard response around benefit changes. Taken together, the results in Chelius (1976, 1982) and Moore and Viscusi (1989) suggest an employer dominated effect rather than the documented moral hazard dominance.

While it is clear the WC system structure through the use of experience rating and federal statues imposes incentives for safety, the academic literature varies in its view of the moral hazard response to WCB. The consensus in the literature indicates that while it does seem that work places are becoming safer as measured by the reduction in real injuries, there is a documented moral hazard response to changes in WCB (Butler and Worrall, 1988; Meyer et al., 1995; Kreuger, 1990; Butler et al., 1997; Butler et al., 1998; Butler, 1994; Ruser, 1991). However, there are others who suggest that the WC systems' incentive for safety is dominant and therefore higher levels of workers' compensation benefits actually save employers money by promoting workplace safety (Chelius, 1976, Chelius, 1982; Moore and Viscusi, 1989). This varying viewpoint motivates our question: Does the safety effect of experience rating dominate the effect of employee moral hazard resulting from a no-fault benefit provision? In answering this question we develop two hypotheses presented in the following section.

CHAPTER 1.3

HYPOTHESES DEVELOPMENT

As the WC legislation developed a structure that moved from a tort system to a no fault system, both employers and workers found favor in the WC system. The system provided benefit to both groups, as workers would be provided timely and dependable benefits, regardless of who was at fault; and the employer's liability was limited. Overall, the WC system and its incorporation of experience rating encouraged employers to provide improved workplace safety. However, overtime it became apparent the expectation of enhanced safety did not take into account factors that would weaken safety, such as moral hazard. Historically, the academic literature has documented the information asymmetries between employer and employee. Primarily, this moral hazard response has been reported in response to WC benefit changes.

While the premise behind the WC system incentivizes for enhanced safety, research is mixed as to the dominant response to changes in WCB. While one stream of findings suggests the moral hazard response dominates the incentive for enhanced safety, others suggest that the employers' incentive to promote workplace safety is greater, as enhanced safety reduces real injury cost and overall insurance cost. Motivated by these two viewpoints, and our ability to explicitly model the impact of actual safety expenditures on loss cost holding benefits constant, we propose two hypotheses: the *moral hazard hypothesis* and the *dominance hypothesis.*

Moral hazard has been tested primarily in the literature by the claims rate response to changes in benefits. The consensus in the literature reports that an increase in benefits leads to an increase in claims (Dionne & St Michel, 1991; Danzon & Harrington, 2001; Butler and Worrall, 1991; Meyer et al., 1995; Kreuger, 1990; Butler et al., 1997; Butler et al., 1998; Butler, 1994; Ruser, 1991). The empirical results indicate that claims frequency is directly related to changes in WCB and that this relationship is particularly evident in injury claims that are hard to diagnose or require a lengthy time away from work. Butler and Worrall (1991) and others, suggest that since WCB compensate employees for not working, there is an inherent behavioral incentive to magnify the severity of injuries, days away from work, and/or misrepresenting the injury incident or location. Based on these finding that WC benefit changes induce moral hazard, we hypothesize the following:

Hypothesis 1- There will be a positive relationship between WCB and loss cost (moral hazard hypothesis).

The alternative to *Hypothesis 1* is that the changes in WCB will have no impact on observed loss cost. Observing no change in loss cost around WC benefit increases would be consistent with the absence of moral hazard in our sample.

Following *Hypothesis 1*, we examine the relation of changes in safety expenditures on changes in loss costs, holding constant benefit changes. Prior studies have differed in their findings of the net effect of safety incentives and the relation between benefit increases and claims/injury frequency or severity (Butler and Worrall, 1991; Moore and Viscusi, 1989). Butler and Worrall, (1991) indicate that while it does seem that work places are becoming safer, the moral hazard response to changes in WCB dominates the inherent incentive in the WC system for an employer to provide enhanced workplace safety, as loss cost increase regardless of safety expenditures. Moore and Viscusi (1989) disagree and document a dramatic safety effect, suggesting that the employers' incentive to promote and enhance safety dominates the moral hazard response to changes in WCB. Taking these competing viewpoints and our ability to explicitly model the impact of actual safety expenditures on loss cost holding benefits constant we hypothesize the following.

Hypothesis 2- There will be a positive relationship between safety expenditure and loss cost, holding benefits constant (dominance hypothesis).

The alternative to *Hypothesis 2* is a negative relationship between safety expenditure and loss cost, holding benefits constant. Observing a negative relationship would indicate that safety is an effective administrative control useful in reducing both real injury cost as well as reducing the moral hazard response to changes in WCB. This would be consistent with Chelius, (1976), Chelius, (1982) and Moore and Viscusi, (1989) who suggest that the WC systems' incentive for safety is dominant and therefore higher levels of workers' compensation benefits actually save employers money by promoting workplace safety.

We expect evaluating these hypotheses and explicitly modeling actual safety expenditures, we will provide the first evidence regarding the impact of actual safety expenditures on moral hazard induced by increases in workers' compensation benefits.

CHAPTER 1.4

SAMPLE AND DATA

A licensed national WC insurer provided data including policy[1], claims[2], underwriting[3], and safety expenditure[4] data, at a policy level (the identities of the insured were omitted from the data). The total sample included 99,824 policies, over a 13 year period, from 1995 to 2007. Our current study incorporated the number of policies per year, written premium, aggregate payroll, safety expenditures per policy, claims count, loss cost, experience rating (EMOD) factor at the beginning of the policy year, and expected loss rate (ELR) factors for each of the governing class codes reflected in the data sample. Supplementing the policy, claims, and underwriting data, is state specific WC disability benefits data across 23 states[5].

[1] Policy Number, Policy Year, Policy Month, Policy Quarter, Policy Size, Policy State, Line of Business, Voluntary/Assigned, Exposure State, Gov Class Code, Class Code, Gov Class Description, Gov Class Group, SCI Code, Hazard Group (1-4), Hazard Group (A-G), Payroll, Premium, Earned Premium, Enforced Premium, Uncollected Premium, Premium Incurred, Deductable, ELR, EMOD, Renewal, Loss Cost, Bill Frequency, Bill Type, Policy Status, Date Effective, Date Cancelled, Date Expired

[2] Policy Number, Policy Year, Claims Number, Loss Year, Accident State, Jurisdiction State, Development Month, ALAE Incurred, ALAE Paid, ALAE Reserve, Indemnity Incurred, Indemnity Paid, Indemnity Reserve, Medical Incurred, Medical Paid, Medical Reserve, Date of Loss, Injury Cause, Injury Type, Claims Size, Closed Status, Body Part, Cause of Loss

[3] Policy Number, Policy Year, Waiver of Subrogation, Employers Limited Liability, Deductable Credit, Misc Factors Applied, Experience Modification, Schedule Rating Credit, Managed Care Credit, Safety Credit, Contractor Credit, Other Credit, Premium Discount, Expense Constant, TRIA Premium

[4] Policy Number, Policy Year, Safety Policy, Overhead Cranes, Accident Investigation, Personal Lift devices, Blood Bourne Pathogens, Personal Protective Equipment, Confined Space Entry, Respiratory, DOT Substance Abuse, Return to Work Program, Drug Sampling, Safety Training, Electrical, Safety Inspections, Fall Protection, Safety Meeting Reporting, Fire Protection and Training, Scaffolding, Forklift, Power Tooling, Slip, Trip, Fall, Hazard Communication, Stairways and Ladders, Hearing Conservation, Trenching, Housekeeping, Job Safety Analysis, Ergonomics, Human Factors, Vehicle Safety, Lockout/Tagout, Machine Guarding, Workplace Security/Violence, Hoist

[5] AK, AL,AR,FL,GA,IA,IL,IN,KS,KY,LA,MD,MN,MO,MS,NC,OK,PA,SC,TN,TX,VA,WI

Testing the *moral hazard* and the *dominance* hypotheses, we examine the relation of changes in loss cost to changes in WC disability benefits, as well as the relation between changes in loss cost and safety expenditures, holding benefits constant. In testing these hypotheses we follow previous literature in defining the dependent and independent control variables. The following section documents the variables.

Dependent Variable

Loss Cost: The actual cost of indemnity payments and allocated loss adjustment expenses. Loss costs do not include overhead costs or profit loadings.

Independent Variables

WCB: Previous analyses have utilized a range of measures for WCB, including the weekly wage replacement rate (Moore and Viscusi, 1989; Chelius, 1982), weekly benefits (Ruser, 1985), and annual payments by industry (Butler, 1994). In most cases, benefits for the most frequent type of claim, temporary total disability, have been used as a proxy for all types of benefits, including those for temporary total, permanent total, and permanent partial disabilities, and for fatality benefits. Viscusi and Moore (1989) documented the high correlations among the various benefit categories that make separation of their effects difficult and indicated the benefit measure using the TTD category is an appropriate measure.

Safety Expenditure: Safety expenditures are the dollar amount spent on the comprehensive safety programs associated with a particular policy. This data is unique to our data sample, as pervious literature has used changes in injury frequency and severity as proxies for safety, and not an actual safety measure.

Payroll: Payroll provides a measure of exposure risk, although an imperfect one. Payroll differs across job class and from employee to employee. However, payroll is the base exposure unit that is used for most WC insurance products and is the best available proxy for the number of workers exposed to injury.

Premium: The amount of earned premium recorded for a policy at the time it is issued. Butler & Worrall (1991) suggest that for some firms the relationship between the loss cost and the size of the premium will be very close.

Claims Count: Claims count is the number of claims per policy in a given year. We postulate that the level of claims should be a function of the number employees (exposure risk), the type of injuries that the employees are exposed to (average risk), and the relative safety record of the employer (relative risk).

Expected Loss Rate (ELR): The average employment-based risk is proxied by the ELR for the governing class code of each employer. The governing class code is not a precise measure of the average loss exposure because it reflects the type of business rather than the direct job-related activities, but it is suggested to provide a practical estimate of average risk for the firm. The governing class code is the primary business of the employer within the state that gets classified, not the separate employments, occupations or operations within the governing type.

Experience Modification Factors (EMOD): The EMOD for each employer provides a measure of relative risk, taking into account the types of employment-related risk present in the employers' business process. The EMOD in our sample was provided by the insurer[6,7]. Employers with higher EMOD factors would be presumed to have greater average loss experience after allowing for the type of business. Experience rating factors change from year to year as the loss experience of the employer is acknowledged in the pricing formula. As an employer's successful safety efforts lead to lower loss costs, the improved safety record is identified and included in the rating formula, resulting in the price of the insurance premium to drop. We would expect to see that increases in the experience modification factor over a period of time would lead to lower loss costs if a firm reduces occupational injuries. We therefore include the change in the EMOD factor and ELR to measure the relationship between increases or decreases of the claims experience and loss cost year to year.

Table 1 presents statistics that describe our sample. Panel A presents the policy characteristics and shows that on average the sample has 7679 policies per year. Average payroll and premium per policy are $27,684 and $392,511, respectively. The average safety expenditure per policy is $612. Panel B. presents the claims and underwriting characteristics. As expected the claims count is proportional related to the policy count. Average claims count in the sample is

[6] Class rates of employers meeting minimum premium requirements are modified based on their relative claims experience over the previous three years. In the United States, the basic formula is: EMOD = (ALR – ELR)/ELR. Where: EMOD = experience rating modification factor, ALR = actual loss ratio, ELR = actuarially computed expected loss ratio (assigned by class).

[7] The EMOD is multiplied times an employer's manual premium (the employers' covered payroll multiplied times the assigned classification rate). If the EMOD is less than 1.0, then the employer's experience-adjusted premium is less than its manual premium. Vice versa, if the EMOD is greater than 1.0 then the employer's experience-adjusted premium is greater than its manual premium. Employers receive an EMOD greater than 1.0 if their claims experience is significantly worse than the average for their particular classification and vice versa. The understanding is that experience rating adjusts for firm-specific risk variation within a given classification.

11,047 with an average loss cost of $11,572. The EMOD and ELR are fairly stable over time 0.939 and 1.22 respectively. These values would be expected if the insurer was doing an appropriate job of adjusting the insurance pricing based on past loss exposures and classifications based on class codes of the job exposures. Panel C presents the benefit data assigned be each of the 23 states in our policy sample. The average WCB is $579 with a minimum benefit of $102.

Table 2 presents statistics that describe the change in variables from year to year. Similar to Table 1 panel A, B, and C present changes in policy, claims/underwriting, and benefit characteristics, respectively. Policy count, payroll, premium, and safety expenditures increase from year to year by 6%, 1%, 18%, and 2%, respectively. Claims counts decreased by 6%, while loss cost increased by an average of 4%. EMOD and ELR were relatively constant with .5% and 1% changes over time, respectively. Lastly, consistent with changes in benefits reported in previous literature the change in benefits over our time period were approximately 4% across max and min WCB and max death benefits.

CHAPTER 1.5

EMPIRICAL METHODOLOGY

In answering our proposed question: does the safety effect of experience rating dominate the effect of employee moral hazard resulting from a no-fault benefit provision; we incorporate univariate and multivariate tests. We first run a univariate analysis of the size of the change in benefits and its relationship to change in average loss cost and average safety expenditures. We calculate and sort benefit changes into quartiles by average change size and run a pair-wise *t*-test of changes in the mean.

Our multivariate analysis is performed with panel data models which allows for regression analysis with both a policy and year dimension. We test whether a fixed or random effects model is appropriate using a Hausman specification test (Hausman 1978). The random effects assumption is that the individual specific effects are uncorrelated with the independent variables, where as the fixed effect assumption is that the individual specific effect is correlated with the independent variables. We find that the random effect assumption does not hold and the random effects model is not consistent. We examine the relation between safety expenditures and loss cost holding WCB constant, *ceteris paribus*, using the panel data fixed effect model:

$$\Delta Avg\ Loss\ Cost_{i,t\text{-}t+1} = \beta_0 + \beta_1 \Delta Payroll_{i,t-1,t} + \beta_2 \Delta Premium_{i,t-1,t} + \beta_3 \Delta Claims\ Count_{i,t-1,t} + \beta_4 \Delta Experience\ Rating_{i,t-1,t} + \beta_5 \Delta Expected\ Loss\ Rate_{i,t-1,t} + \beta_6 \Delta WCB_{i,t-1,t} + \beta_7 \Delta Avg\ Safety\ Expenditure_{i,t-1,t} + \beta_8 \Delta WCB_{i,t-1,t}\ x\ \Delta Avg\ Safety\ Expenditure_{i,t-1,t} + \varepsilon_i \quad (1)$$

The dependent variable is the change in loss cost ($\Delta Avg\ Loss\ Cost_{i,t\text{-}t+1}$)from year t to $t+1$. Following previous literature which documents factors that influence loss cost, we include the changes in: aggregate payroll ($\Delta Payroll_{i,t-1,t}$), earned premium ($\Delta Premium_{i,t-1,t}$), number of claims ($\Delta Claims\ Count_{i,t-1,t}$), experience rating ($\Delta Experience\ Rating_{i,t-1,t}$), and the expected loss rate ($\Delta Expected\ Loss\ Rate_{i,t-1,t}$). Following the consensus in the literature, we include the change in the WC disability benefits ($\Delta WCB_{i,t-1,t}$) to test the moral hazard hypothesis. Unique to our sample is the change in safety expenditures ($\Delta Avg\ Safety\ Expenditure_{i,t-1,t}$), which gives us the ability to explicitly test the impact of safety on loss cost. The variables of interest is the interaction variable between WC benefit changes and safety expenditures ($\Delta WCB_{i,t-1,t}\ x\ \Delta Avg\ Safety\ Expenditure_{\ i,t-1,t}$). This variable directly test the dominance hypothesis and would suggest if moral hazard dominates the safety incentives for an employer inherent in the WC system, the estimate would be to be significantly positive.

We further extend our analysis by taking the multivariate approach in equation 1, within sub samples of our data for hard to diagnose injuries and claims of a lengthened duration. We follow Butler et al. (1997) and define hard to diagnose injuries consist of back injuries and lower and upper extremity sprains and strains. Further, we sort loss cost into quartiles by elapsed claims duration of less than 6 months, 6 months to 12 months, 12 months to 24 months, greater than 24 months.

CHAPTER 1.6

RESULTS

We begin our analysis by examining the moral hazard response to benefit changes and the influence of safety expenditures on that relationship using both univariate and multivariate tests. We also test the relation using a sub sample of claims characteristics that are indicated to be influenced by moral hazard.

Table 3 presents the findings of our univariate analysis of the size of the change in benefits and its relationship to change in average loss cost and average safety expenditures. The average change in benefits in our sample of 23 states is 3.89%. Quartile 1 is a change of less than 1.17%, Quartile 2 a change of greater than 1.17% and less than 3.89%, Quartile 3 a change of greater than 3.89% and less than 5.83%, and Quartile 4 is a benefit change of greater than 5.83%. The univariate analysis indicates that the larger the change in benefits induces a greater change in both loss cost and safety expenditures. These findings are consistent with previous literature suggesting that as WCB increase there is both a moral hazard response (Butler and Worrall, 1991) as well as the potential for enhance workplace safety (Moore and Viscusi, 1989).

Results for our multivariate analysis testing the *moral hazard* and *dominance* hypotheses are presented in Table 4. We postulate that the change in loss cost should be a function of the number employees (exposure risk-payroll), the type of injuries that the employees are exposed to (average risk-ELR), the relative safety record of the employer (relative risk-EMOD), disability benefits, and safety expenditure. Additionally, in the presence of a moral hazard response, we would expect that a change in the WC benefit would be positively related to a change in loss cost. Furthermore, if safety is generally beneficial, we would expect that a change in safety expenditures would have negative relationship to loss cost.

Table 5 columns [1] through [4] indicate our parameter estimates for the change in payroll, premiums, claims count, EMOD, ELR are consistent with the expected signs. A change in payroll has a positive and significant relationship to changes in loss cost, which is expected due to increased exposure levels. Additionally, the change in claims count has a positive and significant relationship as expected due to increase in the number of claims would increase loss cost. Consistent with the literature, changes in EMOD has a negative and significant relationship with change in loss cost. If the average firm's WC costs are directly affected by the change in its EMOD factor, this would lead to a significant safety effect, and would expect to see an inverse relationship between changes in the EMOD and loss cost. This finding is consistent with the notion that as an employer improves the work place safety and reduces injury rates/severity, there is a modification to the pricing of the premium based on past loss history. ELR exhibits a positive and significant relationship to loss cost, indicating as the average risk of the firm increases there is a direct impact on loss cost.

Specifically, Table 5 column [1] that there is a strong positive relationship between changes in WCB and changes in loss cost. We interpret these findings to be consistent with the consensus in the literature regarding a moral hazard response to changes in WCB (Butler and Worrall, 1991; Meyer et al., 1995; Kreuger, 1990; Butler et al., 1997; Butler et al., 1998; Butler, 1994; Ruser, 1991). As such, we fail to reject the *moral hazard* hypothesis. In column [2], we find a negative and significant relationship between changes in safety expenditures and changes in loss cost. The results in column [2] suggest that increases in safety expenditures have a positive impact on loss cost. Column [3] provides the first direct comparison of actual safety expenditures and the influence on the moral hazard response to changes in benefits on loss cost.

Prior findings have inferred the net effect of safety incentives by estimating the relation between benefit increases and claims/injury frequency or severity (Butler and Worrall, 1991; Moore and Viscusi, 1989), while not explicitly modeled the impact of actual safety expenditures. Our findings in column [3] provide initial indications that while the moral hazard exist, increases in safety expenditures reduce the moral hazard response typically seen around changes in disability benefits. This result is of primary importance as it indicates that the safety incentive for an employer potentially dominates the moral hazard response of an employee. In addition, column [4] reports on the relation of changes in safety expenditures on changes in loss costs, holding constant benefit changes. This result suggests that there is a dominating safety effect over that of the moral hazard response. While the moral hazard response is not absolved, there is a reduction in the moral hazard response around WC benefit changes. As a result, we reject the *dominance* hypothesis and find support for Chelius (1977), Chelius (1982) and Moore and Viscusi (1989) who suggest that the WC systems' incentive for safety is dominant and therefore higher levels of workers' compensation benefits actually save employers money by promoting workplace safety. The estimated coefficient of the interaction term is negative and significant. The signs of the individual coefficients remain the same, but $\Delta WCB_{i,t-1,t}$, by itself, no longer appears to be as significant of an explanatory factor. This suggests that WCB affects loss cost through its interaction with safety expenditures, that is, on the marginal propensity to reduce $\Delta Avg\ Loss\ Cost_{i,t-t+1}$. Using these estimates, we estimate the marginal effect of $\Delta WCB_{i,t-1,t}$ upon $\Delta Avg\ Loss\ Cost_{i,t-t+1}$ for three given levels $\Delta Safety\ Expenditures_{i,t-1,t}$; 0.0537 (25% in our sample), 0.0187 (50% in our sample), and 0.0378 (75% in our sample). As such, we expect that a change in safety expenditures of 0.0537 will reduce loss cost by .1160, while a change in safety expenditures of 0.0187 will reduce loss cost by .1331, and a change in safety expenditures of 0.0378 will reduce loss cost by .1238, all other factors held constant. These findings provide evidence that there is a strong incentive to engage in safety practices, not only to reduce loss cost but also reduce the moral hazard response to changes in benefits.

We further extend our analysis by examining the relation between safety expenditures and loss cost holding WCB constant, in a sub sample of claims related to hard to diagnose injuries, fatalities, and claims of a lengthened duration. Table 6 presents the summary statistics related to the sub sample of hard to diagnose injury claims and the length of claims development. Our multivariate results are presented in Table 7. Column [1] provides the results when examining a sub sample of hard to diagnose injury claims. Our results show, similar to that of the complete sample, while the moral hazard response is not absolved, there is a reduction in the moral hazard response around WC benefit through changes in safety expenditures. This result suggests that there is a dominating safety effect over that of the moral hazard response, specifically when examining hard to diagnose injury claims. Columns [2]-[5] present results when partitioning the complete sample into quartiles based on claims development. These partitions are < 6 months, 6-12 months, 12-24 months, and > 24 months. We find that for low claims development durations, there was not a moral hazard response to benefit changes, whereas moral hazard was reported as claims duration increased. Of particular interest was the finding that changes in safety expenditures had a positive impact on the reduction of real injuries, while at the same type reducing the documented moral hazard response to benefit changes.

CHAPTER 1.7

CONCLUSIONS

The results of this study indicate that changes in safety expenditures both reduce the level of loss cost, while reducing the level of moral hazard response to changes in disability benefits. The latter finding is of primary interest as it supports existing literature indicating that safety has a beneficial effect on WC cost. More importantly, while previous literature indicate that the moral hazard effect dominates the safety incentive of an employer, the current findings support the notion that safety incentives actually may reduce the moral hazard response generated by changes in benefits.

Our initial analysis suggests that EMOD and ELR do have the intended effect of encouraging employers to reduce loss cost. More specifically, our analysis yields supporting evidence that increases in EMOD factors lead to decreases the loss cost in subsequent years. We also find that employer size, as measured by payroll, is positively related to loss cost, while premium has no direct statistical relation to the reduction of loss cost. Furthermore, as claims increase the results indicate an increase in loss cost, which is consistent with the notion that the greater number of claims increases the loss cost levels of the firm.

Our study poses and addresses an important empirical question: Does the safety effect of experience rating dominate the effect of employee moral hazard resulting from a no-fault benefit provision? Using our unique dataset we are able to estimate the impact of changes in safety expenditures on changes in loss costs, holding constant benefit changes. Subsequently, we show that safety expenditures play a positive role in reducing the moral hazard response to changes in

WCB. Prior studies have inferred the net effect of safety incentives by estimating the relation between benefit increases and claims/injury frequency or severity (Butler and Worrall, 1991; Moore and Viscusi, 1989). However, these studies have not explicitly modeled the impact of actual safety expenditures.

While rising claims costs could lead one to the mistaken belief that the WC system does not provide an incentive to reduce real injuries, or that an employee's incentive to bear more real risk is stronger than an employer's incentive to reduce injuries, the current results indicate that the employer’s incentive for safety is not unfounded. While the evidence is virtually unanimous in previous studies showing that employee effects dominate, the current study indicates that while the moral hazard response is not eliminated, changes in safety expenditures significantly reduce the moral hazard response. Our findings provide some of the first evidence supporting the idea that safety expenditures are beneficial and have a positive impact on reducing both loss cost and the moral hazard response to changes in benefits.

Table 1. The table presents means and definitions for each of the variables.

Variable	***Definition***	***Mean***	
Policy Count	Number of policies		7679
Premium	Dollar amount of premium recorded for a policy at the time it is issued	$	27,684
Payroll	Measure of exposure risk proxied by aggregate payroll per policy	$	392,511
Safety Expenditure	Dollar amount of comprehensive safety program per policy	$	612
Claims Count	Number of claims per policy		11,047
Loss Cost	Incurred loss cost over the subsequent year per policy	$	11,572
EMOD*	Measure of relative risk based on the policy holders business process		0.939
ELR*	Measure of employment-based risk for the governing class code of each policy		1.22
Max Disability Benefit**	Weekly maximum disability rate within the temporary total disability category	$	579
Min Disability Benefit**	Weekly minimum disability rate within the temporary total disability category	$	102
Max Death Benefit**	Maximum death benefit	$	579

* Factors have been calculated in the private data sample. Calculations are footnoted in the methods section.

**Weekly rate schedules based on the exposure state (N=23) of the policy

Table 2. Summary Statistics

Panel A. provides the policy specific characteristics. Policy count details the number of policy in the sample. Premium is the amount of premium recorded for a policy at the time it is issued. Payroll provides a measure of exposure risk proxied by aggregate payroll. Safety expenditures are the dollar amount spent on the comprehensive safety programs associated with a particular policy. Panel B. reports the claims/underwriting characteristics of our sample. Claims count is the number of claims per policy in a given year. The average employment-based risk is proxied by the ELR for the governing class code of each employer. The EMOD factor for each employer provides a measure of relative risk, taking into account the types of employment-related risk present in the employers' business process. Panel C. reports the benefit characteristics. Maximum benefit is a measure using the weekly maximum disability rate within the temporary total disability category. The benefit data is recorded from each of the 23 states (in our sample) rate schedules based on the exposure state of the policy. Minimum and maximum death benefits are reported the same as maximum benefits.

Panel A. Policy Characteristics

Year	*Policy Count*	*Avg Premium*			*Avg Payroll*			*Avg Safety Expenditure*		
		25%	*50%*	*75%*	*25%*	*50%*	*75%*	*25%*	*50%*	*75%*
1995	2229	8755	28811	65445	889	1289	3106	217	598	1392
1996	3350	8717	20068	65364	3708	10162	31515	230	432	794
1997	6201	9162	18097	67106	166770	310139	1175025	241	450	563
1998	9632	8736	16404	68958	211185	450642	2176476	231	420	625
1999	14964	8447	16937	70223	242267	549132	2286795	261	517	833
2000	13447	8331	18516	68293	194728	506901	1877192	284	533	999
2001	8457	8294	21644	61583	117263	363780	1163457	292	541	1195
2002	6480	8374	27886	65706	98094	383350	995683	311	611	1672
2003	6454	9070	33928	67138	102806	446457	969018	326	677	2024
2004	6673	9232	37415	70697	106445	492783	975322	371	743	2300
2005	6954	9912	40806	72458	124537	532784	994184	386	792	2648
2006	7226	9310	40979	70618	118238	544346	974645	418	816	2936
2007	7757	8393	38406	67414	107075	510875	948698	426	829	3371
Mean	7679	8826	27684	67769	122616	392511	1120855	307	612	1643

Panel B. Claims/Underwriting Characteristics

Year	*Claims Count*	*Avg Loss Cost*			*EMOD*	*ELR*
		25%	*50%*	*75%*		
1995	3616	2298	9527	269333	0.941	1.23
1996	4926	2069	7418	168491	0.928	0.95
1997	11326	3839	6171	405194	0.936	0.89
1998	20436	2495	4651	382278	0.943	0.94
1999	33169	1802	5412	505592	0.918	0.91
2000	22783	2759	6896	585665	0.967	0.96
2001	9253	3162	8960	317005	0.941	1.16
2002	6229	3347	11400	771112	0.938	1.38
2003	5926	3094	14099	847534	0.953	1.43
2004	6605	3421	16937	339762	0.926	1.50
2005	6759	5188	20355	647835	0.937	1.52
2006	6301	3144	16859	456396	0.934	1.51
2007	6283	3296	21747	521461	0.944	1.48
Mean	11047	3070	11572	478281	0.939	1.220

Panel C. Disability Benefits Characteristics

Year	*Avg Max Benefit*			*Avg Min Benefit*		
	25%	*50%*	*75%*	*25%*	*50%*	*75%*
1995	326	444	525	68	83	126
1996	338	462	540	71	85	130
1997	351	491	553	74	89	136
1998	366	507	573	77	91	140
1999	383	542	602	81	96	146
2000	401	570	631	84	99	151
2001	417	590	668	87	103	156
2002	432	591	700	90	107	161
2003	440	628	722	93	108	167
2004	449	641	740	96	110	173
2005	467	661	770	99	114	179
2006	483	680	801	102	117	188
2007	510	717	848	107	122	194
Mean	413	579	667	87	102	157

Table 3. Changes in summary statistics

Panel A. provides the policy specific characteristics, panel B reports the claims/underwriting characteristics, and panel C reports benefit characteristics. The variables are defined as the change in the summary statistics variables from table 1.Policy count details the number of policy in the sample. Premium is the amount of premium recorded for a policy at the time it is issued. Payroll provides a measure of exposure risk proxied by aggregate payroll. Safety expenditures are the dollar amount spent on the comprehensive safety programs associated with a particular policy. Panel B. reports the claims/underwriting characteristics of our sample. Claims count is the number of claims per policy in a given year. The average employment-based risk is proxied by the ELR for the governing class code of each employer. The EMOD factor for each employer provides a measure of relative risk, taking into account the types of employment-related risk present in the employers' business process. Panel C. reports the benefit characteristics. Maximum benefit is a measure using the weekly maximum disability rate within the temporary total disability category. The benefit data is recorded from each of the 23 states (in our sample) rate schedules based on the exposure state of the policy. Minimum and maximum death benefits are reported the same as maximum benefits.

Panel A. Changes in Policy Characteristics

	ΔPolicy Count	*ΔAvg Premium*			*ΔAvg Payroll*		*Safety Expenditures*	
Year		*25%*	*50%*	*75%*	*25%*	*50%*	*50%*	*75%*
1995	-	-	-	-	-	-	-	-
1996	0.3346	-0.0044	-0.4357	-0.0012	0.7602	0.8732	-0.3843	-0.7531
1997	0.4598	0.0486	-0.1089	0.0260	0.9778	0.9672	0.0400	-0.4098
1998	0.3562	-0.0488	-0.1032	0.0269	0.2103	0.3118	-0.0714	0.0985
1999	0.3563	-0.0342	0.0315	0.0180	0.1283	0.1794	0.1876	0.2505
2000	-0.1128	-0.0139	0.0853	-0.0283	-0.2441	-0.0833	0.0300	0.1662
2001	-0.5900	-0.0045	0.1445	-0.1090	-0.6606	-0.3934	0.0148	0.1639
2002	-0.3051	0.0096	0.2238	0.0627	-0.1954	0.0510	0.1146	0.2851
2003	-0.0040	0.0767	0.1781	0.0213	0.0458	0.1414	0.0975	0.1736
2004	0.0328	0.0175	0.0932	0.0503	0.0342	0.0940	0.0888	0.1203
2005	0.0404	0.0686	0.0831	0.0243	0.1453	0.0751	0.0619	0.1314
2006	0.0376	-0.0647	0.0042	-0.0261	-0.0533	0.0212	0.0294	0.0980
2007	0.0685	-0.1093	-0.0670	-0.0475	-0.1043	-0.0655	0.0157	0.1290
Mean	0.0562	-0.0049	0.0107	0.0015	0.0870	0.1810	0.0187	0.0378

	ΔClaims Count	*ΔAvg Loss Cost*			*ΔEMOD*	*ΔELR*
Year		*25%*	*50%*	*75%*		
1995	-	-	-	-		
1996	0.2659	-0.1107	-0.2843	-0.5985	-0.014	-0.30
1997	0.5651	0.4611	-0.2021	0.5842	0.009	-0.07
1998	0.4458	-0.5387	-0.3268	-0.0599	0.007	0.05
1999	0.3839	-0.3846	0.1406	0.2439	-0.027	-0.03
2000	-0.4559	0.3469	0.2152	0.1367	0.051	0.05
2001	-1.4622	0.1275	0.2304	-0.8475	-0.028	0.18
2002	-0.4855	0.0553	0.2140	0.5889	-0.003	0.16
2003	-0.0511	-0.0818	0.1914	0.0902	0.016	0.03
2004	0.1028	0.0956	0.1676	-1.4945	-0.029	0.05
2005	0.0228	0.3406	0.1679	0.4755	0.012	0.01
2006	-0.0727	-0.6501	-0.2074	-0.4195	-0.003	0.00
2007	-0.0029	0.0461	0.2248	0.1248	0.011	-0.02

Mean	-0.0620	-0.0244	0.0443	-0.0980	0.00002	0.01

Panel C. Changes in Disability Benefits Characteristics

	ΔAvg Max Benefit			*ΔAvg Min Benefit*			*ΔAvg Death Benefit*		
Year	*25%*	*50%*	*75%*	*25%*	*50%*	*75%*	*25%*	*50%*	*75%*
1995	-	-	-	-	-	-	-	-	-
1996	0.0355	0.0374	0.0278	0.0380	0.0256	0.0308	0.0355	0.0374	0.0278
1997	0.0370	0.0597	0.0235	0.0366	0.0423	0.0441	0.0370	0.0597	0.0235
1998	0.0410	0.0323	0.0349	0.0447	0.0311	0.0286	0.0410	0.0323	0.0349
1999	0.0444	0.0643	0.0482	0.0481	0.0446	0.0411	0.0444	0.0643	0.0482
2000	0.0449	0.0491	0.0460	0.0374	0.0372	0.0331	0.0449	0.0491	0.0460
2001	0.0384	0.0335	0.0554	0.0327	0.0346	0.0321	0.0384	0.0335	0.0554
2002	0.0347	0.0007	0.0457	0.0301	0.0372	0.0311	0.0347	0.0007	0.0457
2003	0.0182	0.0595	0.0305	0.0307	0.0087	0.0359	0.0182	0.0595	0.0305
2004	0.0200	0.0206	0.0243	0.0313	0.0221	0.0347	0.0200	0.0206	0.0243
2005	0.0385	0.0307	0.0390	0.0377	0.0316	0.0335	0.0385	0.0307	0.0390
2006	0.0331	0.0273	0.0387	0.0279	0.0250	0.0479	0.0331	0.0273	0.0387
2007	0.0529	0.0519	0.0554	0.0435	0.0438	0.0309	0.0529	0.0519	0.0554
Mean	0.0366	0.0389	0.0391	0.0365	0.0320	0.0353	0.0366	0.0389	0.0391

Table 4. Univariate Analysis of the Size of a Benefit Change on Change in Loss Cost and Change in Safety Expenditure

Reported are the findings of our univariate analysis of the size of the change in benefits and its relationship to change in average loss cost and average safety expenditures. We calculate and sort benefit changes into quartiles by average change size. The average change in benefits in our sample of 23 states is 3.89%. Quartile 1 is a change of less than 1.17%, Quartile 2 a change of greater than 1.17% and less than 3.89%, Quartile 3 a change of greater than 3.89% and less than 5.83%, and Quartile 4 is a benefit change of greater than 5.83%. P-values are reported in parentheses. ***,**,* represent statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

ΔAvg Max Benefit	*Quartile 1 (< 1.17%)*	*Quartile 2 (>1.17%, <3.89%)*	*Quartile 3 (>3.89%, <5.83%)*	*Quartile 4 (>5.83%)*	*Difference Q2-Q1*	*Difference Q3-Q2*	*Difference Q4-Q3*	*Difference Q4-Q1*
ΔAvg Loss Cost	0.0406	0.0687	0.1143	0.1943	0.0281	0.0456	0.08*** (0.006)	0.1537*** (0.002)
ΔAvg Safety Expenditures	0.0323	0.0709	0.1287	0.2064	0.0386	0.0578	0.0777** (0.011)	0.1741*** (0.000)

Table 5. Regression Results
The table reports the results from estimating the following equation.

$$\Delta Avg\ Loss\ Cost_{i,t-t+1} = \beta_0 + \beta_1 \Delta Payroll_{i,t-1,t} + \beta_2 \Delta Premium_{i,t-1,t} + \beta_3 \Delta Claims\ Count_{i,t-1,t} + \beta_4 \Delta Experience\ Rating_{i,t-1,t} + \beta_5 \Delta Expected\ Loss\ Rate_{i,t-1,t} + \beta_6 \Delta Avg\ Max\ Benefit_{i,t-1,t} + \beta_7 \Delta Avg\ Safety\ Expenditure_{i,t-1,t} + \beta_8 \Delta Avg\ Max\ Benefit_{i,t-1,t}\ x\ \Delta Avg\ Safety\ Expenditure_{i,t-1,t} + \varepsilon_i \quad (1)$$

Our dependent variable is the change in loss cost for each claim in the sample in the subsequent year. $\Delta Avg\ Loss\ Cost_{i,t-t+1}$=the average loss cost over the subsequent year. $\Delta Payroll_{i,t-1,t}$ is the change in payroll from the prior year to the current year. $\Delta Premium_{i,t-1,t}$ is the change in the premium from the prior year to the current year. $\Delta Claims\ Count_{i,t-1,t}$ is the change in the claims from the prior year to the current year. $\Delta Experience\ Rating_{i,t-1,t}$ is the change in the EMOD factor from the prior year to the current year. $\Delta Expected\ Loss\ Rate_{i,t-1,t}$ is the change in the ELR factor from the prior year to the current year. $\Delta Avg\ Max\ Benefit_{i,t-1,t}$ is the change in the maximum WC benefit from the prior year to the current year. $\Delta Avg\ Safety\ Expenditure_{i,t-1,t}$ is the change in the safety expenditures per policy from the prior year to the current year. P-values are reported in parentheses. ***,**,* represent statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	ΔAvg Loss Cost			
	[1]	[2]	[3]	[4]
Intercept	0.2974***	0.3143***	0.3019***	0.2879***
	(0.000)	(0.000)	(0.000)	(0.000)
ΔPayroll	0.1979***	0.1884***	0.1817***	0.1892***
	(0.000)	(0.000)	(0.000)	(0.000)
ΔPremium	0.2216	0.2109	0.1984	0.2201
	(0.225)	(0.193)	(0.248)	(0.316)
ΔClaims Count	0.3597***	0.3016***	0.2944***	0.2717***
	(0.000)	(0.000)	(0.000)	(0.000)
ΔExperience Rating	-0.1856***	-0.1687***	-0.1536***	-0.1461***
	(0.000)	(0.000)	(0.000)	(0.000)
ΔExpected Loss Rate	0.0997*	0.0904*	0.0811*	0.0806*
	(0.091)	(0.078)	(0.061)	(0.104)
ΔAvg Max Benefit	0.2085***		0.1638*	0.1422*
	(0.000)		(0.087)	(0.094)
ΔAvg Safety Expenditure		-0.3741***	-0.3421***	-0.3318***
		(0.000)	(0.000)	(0.000)
ΔAvg Max Benefit x ΔAvg Safety Expenditure				-0.4866***
				(0.000)
Adj R^2	0.1672	0.1944	0.2221	0.2593
Observations	82,704	82,704	82,704	82,704

Table 6. Summary statistics from hard to diagnose claims and claims duration.
Panel A. provides hard to diagnose claims characteristics. Claims count is the number of hard to diagnose claims per policy in a given year. Average loss cost is the average actual cost of indemnity payments and allocated loss adjustment expenses. Panel B presents total claims and average loss cost portioned by the length of duration of a closed claim.

Panel A. Hard to Diagnose Injuries: Claims Characteristics

Year	Claims Count	Avg Loss Cost
1995	345	14,814
1996	722	8,634
1997	1,297	5,356
1998	2,723	3,827
1999	4,912	3,588
2000	6,203	3,781
2001	3,822	5,776
2002	1,766	7,049
2003	1,312	11,533
2004	1,304	14,645
2005	1,351	19,606
2006	1,506	13,133
2007	1,325	15,641
Mean	2,199	9,799

Panel B. Duration of Claims Develeopment to Closing

	< 6 Months		6-12 months		12-24 Months		> 24 Months	
Year	Claims Count	Avg Loss Cost	Claims Count	Avg Loss Cost	Claims Count	Avg Loss Cost	Claims Count	Avg Loss Cost
1995	85	9,368	943	11,595	1,905	10,880	2,191	10,163
1996	185	7,688	1,651	9,339	2,797	8,345	3,229	7,648
1997	312	2,776	3,188	6,454	5,671	6,334	6,627	6,435
1998	694	2,032	6,577	4,203	11,207	4,443	12,859	4,473
1999	1,250	2,280	11,641	4,456	19,837	4,741	22,485	4,950
2000	1,610	1,934	13,626	5,120	21,020	6,376	21,336	6,466
2001	1,187	3,701	7,729	7,308	10,937	8,179	11,917	8,443
2002	550	4,821	3,908	7,490	6,145	9,226	6,875	9,646
2003	404	7,318	2,848	11,633	4,569	13,338	5,193	13,154
2004	345	10,301	3,016	14,666	5,029	15,302	5,640	15,502
2005	374	6,391	3,001	20,193	5,063	18,956	5,706	18,947
2006	406	6,054	3,255	14,615	5,132	15,228	5,779	15,691
2007	396	6,748	3,159	18,634	4,973	20,161	5,616	20,706
Mean	600	5,493	4,965	10,439	8,022	10,885	8,881	10,940

Table 7. Regression Results
The table reports the results from estimating the following equation.

$$\Delta Avg\ Loss\ Cost_{i,t-t+1} = \beta_0 + \beta_1 \Delta Payroll_{i,t-1,t} + \beta_2 \Delta Premium_{i,t-1,t} + \beta_3 \Delta Claims\ Count_{i,t-1,t} + \beta_4 \Delta Experience\ Rating_{i,t-1,t} + \beta_5 \Delta Expected\ Loss\ Rate_{i,t-1,t} + \beta_6 \Delta Avg\ Max\ Benefit_{\ i,t-1,t} + \beta_7 \Delta Avg\ Safety\ Expenditure_{i,t-1,t} + \beta_8 \Delta Avg\ Max\ Benefit_{\ i,t-1,t}\ x\ \Delta Avg\ Safety\ Expenditure_{\ i,t-1,t} + \varepsilon_i \quad (1)$$

Our model specifications are identical to that of Table 5. Column 1 presents the results in our sub sample of hard to diagnose (HTD) injuries. Columns 2-5 partition the sub sample into the length of claims development till claims closing. These partitions are < 6months, 6-12 months, 12-24 months, and > 24 months. P-values are reported in parentheses. ***,**,* represent statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	ΔAvg Loss Cost				
	[HTD]	[< 6]	[6-12]	[12-24]	[> 24]
Intercept	0.4617***	0.2784***	0.2893***	0.2774***	0.2956***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΔPayroll	0.2613***	0.3106***	0.2746***	0.2459***	0.2827***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΔPremium	0.1487*	0.2561	0.2713	0.2558	0.2763
	(0.094)	(0.263)	(0.184)	(0.401)	(0.289)
ΔClaims Count	0.2129***	0.2591***	0.2743***	0.2999***	0.3358***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΔExperience Rating	-0.1487***	-0.2103***	-0.1648***	-0.1788***	-0.2013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΔExpected Loss Rate	0.1171**	0.0841**	0.0976*	0.0755**	0.0717**
	(0.047)	(0.034)	(0.082)	(0.038)	(0.027)
ΔAvg Max Benefit	0.2179*	0.1684	0.1623*	0.1894*	0.1907*
	(0.068)	(0.214)	(0.086)	(0.073)	(0.084)
ΔAvg Safety Expenditure	-0.2641***	-0.1867**	-0.2106**	-0.2188***	-0.2468***
	(0.000)	(0.032)	(0.047)	(0.000)	(0.000)
ΔAvg Max Benefit x ΔAvg Safety Expenditure	-0.3941***	-0.2737**	-0.2943**	-0.3449***	-0.4064***
	(0.000)	(0.044)	(0.032)	(0.000)	(0.000)
Adj R^2	0.2341	0.1483	0.1866	0.2243	0.2497
Observations	29,844	43,632	38,532	43,452	21,410

ESSAY 2:

INFORMATION AND INSURER FINANCIAL STRENGTH RATINGS: DO SHORT SELLERS ANTICIPATE RATINGS CHANGES?

CHAPTER 2.1

INTRODUCTION

Research regarding the financial strength ratings of insurance companies has received recent considerable attention. Doherty and Phillips (2002) argue that insurers attempt to market their financial strength ratings as a signal of the firm's financial strength. Pottier and Sommer (1999) suggest that investors use financial strength ratings of public insurance companies as measures of risk, while Parekh (2006) suggests that insurers with financial strength ratings above some specified threshold are more popular than other insurers. Halek and Eckles (2010) find that stock prices of insurance companies tend to move in the direction of ratings changes, particularly for unfavorable ratings changes, thus indicating that ratings provide informational value to the market. The purpose of this study is to test whether the price decline precipitated by ratings downgrades is anticipated by short sellers, who are found to have an unusual ability to acquire private information about future news events that adversely affect stock prices.

Diamond and Verrecchia (1987) initially conjecture that short sellers are sophisticated investors and possess information about future firm performance and the true value of stocks. This assertion has been empirically supported by numerous studies that find short selling is inversely related to subsequent returns (Senchack and Starks, 1993; Aitken, Frino, McCorry, and Swan, 1998; Desai, Ramesh, Thiagarajan, and Balachandran, 2002; Boehmer, Jones, and Zhang, 2008; Engelberg, Reed, and Riggenberg, 2010; Christophe, Ferri, and Angel, 2004; Christophe, Ferri, and Hsieh, 2010). However, observing a negative relation between short selling and subsequent returns is not necessarily equivalent to finding short sellers to be privately informed.

Short sellers' ability to predict negative returns may arise from their superior ability to process public information. Indeed, Engelberg et al. (2010) show that the return predictability of short sellers is markedly higher on days with information-rich announcements than on non-event days; mainly driven by short sellers' superior ability to process publically available information. Therefore, determining whether short sellers are privately informed requires examining short selling behavior before an information-rich event. Christophe et al. (2004) and Christophe et al. (2010) examine shorting activity prior to earnings announcements and analyst recommendations, respectively, and find that short selling is abnormally high prior to both unfavorable earnings announcements and downward analyst recommendation changes. When examining short selling around insider sales, Khan and Lu (2008) find abnormal short selling prior to insider sales. These previous findings substantiate the assertion short sellers are sophisticated traders around information rich events.

While there is a foundation of research suggesting short sellers are sophisticated; a recent stream of literature suggest that short sellers are no more sophisticated prior to informational events than other traders (Daske, Richardson, and Tuna, 2005; Boehmer and Wu, 2008; Chakrabarty and Shkilko, 2008; Blau and Wade, 2011; Blau and Pinegar, 2010). Daske et al. (2005) and Boehmer and Wu (2008), show that short sellers are not able to predict negative announcements and instead increase their shorting activity in response to announcements. Blau and Wade (2011) find the short-selling patterns surrounding both analyst downgrades and upgrades are remarkably symmetric indicating that short sellers during the pre-recommendation period are not unusually informed about the direction of upcoming recommendation changes. Their findings indicate that short selling prior to analyst recommendations is more likely speculative than informed. Blau and Pingear (2010) find that short selling surges after both positive and negative announcements and that short selling immediately before negative announcements is less able to predict future returns than short selling during more normal times. Chakrabarty and Shkilko (2008) only find abnormal short selling on days with insider sales and the event-day short selling is not able to identify the insider sales that have the largest future stock price decline, suggesting that the ability of short sellers to predict the negative news in insider trades is selective at best. These studies begin to question the informativeness of short sellers prior to negative news events.

Our motivation for the current study is driven by the conflicting findings around short sellers and their ability to capitalize on negative news announcements, combined with those of Halek and Eckles (2010) indicating insurer financial strength ratings provide informational value to the market, specifically that of unfavorable ratings. Insurer financial strength rating (IFSR) downgrades make tests of informed short selling relevant for two reasons. First, IFSR announcements are not presented on a fixed calendar schedule, in turn IFSR are less predictable than other types of announcements such as earnings or analysts' recommendations. Secondly, IFSR are focused on insurance companies. Insurance companies vary in their level of opaqueness as their asset and liability structure is focused in different lines of insurance business that vary in the level of uncertainty (Ross, 1989; Baranoff and Sager, 2002; Zhang, Cox, and Van Ness, 2009). The opaqueness of the liabilities and assets of an insurer may affect the amount of information short sellers have to capitalize on, based on uncertainty of claims payouts. Thus, IFSR changes provide a robust framework for testing whether short sellers have a superior ability to process information. If short sellers are better able to process the information contained in IFSR, we expect to see abnormally high short selling before IFSR downgrades, regardless of the degree of opaqueness in the insurers asset and liability structure.

Using a sample of 25 A.M. Best ratings downgrades announced between January 1, 2005 and December 31, 2006, we examine shorting activity surrounding IFSR changes. We first examine short selling prior to IFSR downgrades to test if short sellers are able to predict IFSR downgrades, referred to as the *sophisticated trading* hypothesis. Second, we examine the relation between abnormal short selling and the degree of opaqueness of downgraded insurers to determine whether short sellers are unusually sophisticated in their response to the downgrade, which we denote as the *front running* hypothesis. Our results are interesting. First, in support of *sophisticated trading* hypothesis, we find evidence of abnormal short selling prior to IFSR downgrades. Our tests are robust to the standardized short ratio and standardized short turnover measures of short selling. Observing abnormal levels of shorting activity during the pre-IFSR period indicates that short sellers' are sophisticated in processing information related to the IFSR. Secondly, contrary to the *front running* hypothesis, we find opaqueness negatively affects the level of short selling activity. If short sellers are recipients of private information or are unusually sophisticated prior to IFSR downgrades, then the *front running* hypothesis predicts abnormally high short selling prior to IFSR downgrades regardless of the degree of opaqueness of the downgraded insurer.

An observation of Halek and Eckles (2010) reveals that returns in the two days prior to downgrades become significantly negative suggesting that some sophisticated investors anticipate the price reaction to downgrades. Our univariate tests reveal that, indeed, market-adjusted returns begin to move in the direction of the ratings change beginning two days prior to the downgrade. Interestingly, we further show that short sellers have an impressive ability to predict downgrades as short selling begins to increase a day before the ratings downgrade occurs.

In our multivariate tests we find that short selling is abnormally high on the day prior to downgrades, ceteris paribus. In addition, we examine the documented positive relation between short selling and contemporaneous returns. Consistent with Diether, Lee, and Werner (2009), we find that short sellers are generally contrarian in contemporaneous returns. However, on the day prior to the downgrade, we find that short sellers become less contrarian as the relation between short selling and current returns weakens. This latter result indicates that short sellers become less concerned about contemporaneous price movements and more concerned with the upcoming price reaction to the ratings downgrade. Our analysis of short selling around ratings downgrades is consistent with the idea that information about the ratings change is available to short sellers before the change is publicly observed, although other explanations exist. These findings are relevant to those in Halek and Eckles (2010) as we begin to see that not only do prices respond in the direction of the ratings change, but the price response occurs prior to the public observation of the downgrade and is anticipated by sophisticated short sellers.

We further extend our analysis by examining the relation between abnormal short selling and the degree of opaqueness of downgraded insurers. While insurers are similar to that of banks in opaqueness of their assets (Ross, 1989; Polonchek and Miller, 1999), the opaqueness of insurers' liabilities is unique (Babbel and Merrill, 2005; Baranoff and Sager, 2002; Zhang et al. 2009). Overall, the literature suggests that insurance companies present an increased degree of information asymmetry between claimholders, investors and the firm due to opaqueness of their liability and asset structure. Most recently, Zhang et al. (2009) found that the adverse selection component of the spread, which measures the level of asymmetric information between market makers and traders, is increasing in the level of firm opaqueness. If short sellers are recipients of private information or are unusually sophisticated prior to IFSR downgrades, then the *front* *running* hypothesis predicts abnormally high short selling prior to IFSR downgrades regardless of the degree of opaqueness of the downgraded insurer. Following the methods of Zhang et al. (2009) in defining opaqueness, we reject the *front running* hypothesis by finding the degree of opaqueness of an insurer's liabilities and assets negatively affects the level of short selling in the insurer's stock.

As previously mentioned Christophe et al. (2010) contend that abnormal pre-downgrade shorting activity is consistent with informed investors acquiring information about an upcoming downgrade and establish short positions prior to the release date in order to take advantage of the price reaction to the recommendation change. However, Blau and Wade (2011) argue that observing abnormal short selling prior to downgrades is not equivalent to determining that short sellers can acquire information, as they show short-selling patterns surrounding both analyst downgrades and upgrades are remarkably symmetric. For robustness, we follow Blau and Wade (2011) and examine short selling around favorable IFSR changes. We find abnormally low short selling on days prior to IFSR upgrades and that short selling spikes on days with IFSR upgrades. In our multivariate tests, we find the estimate for the upgrade dummy variable, capturing the upgrade event day, becomes negative suggesting that short sellers are not necessarily concerned about the upgrade as much as they are about the price reaction to the upgrade. Combined with the findings in Halek and Eckles (2010), who document little or no price response to ratings upgrades, our results show that short sellers either attenuate the insignificant price reaction or short sellers recognize that upgrades do not provide valuable information to the market that has not already impacted prices. We are left to conclude that pre-IFSR downgrade short selling is motivated by some amount of tradable information rather than speculation.

The next section reviews related prior literature. The following section develops our hypotheses, and sample and data are introduced in the subsequent section. The next two sections present our empirical methodology and discuss our results. The final section concludes.

CHAPTER 2.2

PRIOR LITERATURE

Financial strength ratings have been thought of as summary measure of insolvency risk for a number of years (Pottier and Sommer, 1999). The rating provides a rating agency's opinion of the insurer's overall financial strength and ability to meet its policyholder obligations. This financial strength rating has been related to a myriad of characteristic, such as capitalization, liquidity and size (Pottier, 1998). Financial strength ratings are assigned to both individual companies and to consolidated groups of insurance firms. These ratings are important because they influence the price insurers can charge for their policies (Doherty and Phillips, 2002).

Insurance company ratings, specifically those issued by A.M. Best, are vitally important to consumers, insurers, investors, regulators, and insurance brokers and agents. Insurance consumers use them in determining which insurance companies they purchase coverage and/or determining the cost they are willing to pay for insurance from their chosen company. The ratings are as valuable, if not more, to the insurers who use the ratings for advertising purposes in order to convey the company's financial strength and ability to meet obligations to their policy holders. Often during the individual insurance purchasing process, brokers and agents recommend coverage based on the ratings provided for a specific company, whereas corporate insurance consumers require that all their insurers be highly rated. Investors identify ratings as an indication of investment risk (Sclafane, 2000) and regulators incorporate ratings in evaluating insurer financial strength (Schwartz, 1994).

While the ratings are utilized for different purposes, the ratings contain new information which may be of interest to individuals or companies incorporating the ratings into their decision making process. The informational content of ratings is apparent when looking at the reaction the capital markets have to a ratings change. Halek and Eckles (2010) hypothesize that a rating agency possesses superior information relative to the public and that its ratings announcements add to the public information related to an insurer. In testing their hypotheses, Halek and Eckles (2010) find that stock prices of insurance companies tend to move in the direction of ratings changes, particularly for unfavorable ratings changes, thus indicating that ratings provide informational value to the market. As further evidence of the information in ratings, Pottier and Sommer (1999) suggests that the ratings themselves may be predicted by publicly available information such as insurer size, profitability and growth in premiums written.

In regards to the information contained in a ratings change, investors may be concerned with rating changes due to the potential changes insurers' future cash flows. Doherty and Phillips (2002) suggest that during the period in which A.M. Best changed their ratings standards, insurers significantly increasing their working capital. Furthermore, Doherty and Phillips (2002) suggested that losing a high financial strength rating had a significant impact on an insurer, and that rating agencies play an important function in reducing the asymmetric information between the insurers and consumers. Cummins and Danzon (1997) observe that insurance premiums are positively related to financial strength ratings, while Pottier (1998) indicate that adverse rating changes had significant predicting power for forecasting life insurer insolvency. These previous findings combined with those of Halek and Eckles (2010) indicate that ratings provide information to investors on the financial strength of an insurer.

In theory, if trading activity is combined with private information, then the outcome of the trading activity may well make possible price discovery or reveal future price movements. As such, investors who have realization of private information can decide to be active and take advantage of on their private information. Evidence supporting the idea that short sellers are informed is robust. Diamond and Verrecchia (1987) predicts that unanticipated increases in short selling will be followed by negative returns. Further Diamond & Verrecchia (1987) conclude that short sellers possess superior information about future stock performance. Empirical tests of the Diamond & Verrecchia (1987) hypothesis confirm that short sellers are sophisticated and possess superior information about the true value of stocks. Diamond and Verrecchia (1987) hypothesis is based on the thought that short sellers face borrowing constraints and when these constraints are severe, short selling becomes costly. As such, short sellers who are willing to face these costs must be informed about future downward price movements to make short selling less risky.

Empirical results consistently find that current short selling relates inversely with future returns indicating that short sellers are informed (Senchack and Starks, 1993; Aitken et al. 1998; Desai et al. 2002; Boehmer et al. 2008; Engelberg et al. 2010; Christophe et al. 2004; Christophe et al. 2010). While short sellers appear to be informed about future downward price movements, the question as to whether short sellers are informed about upcoming negative news contained in firm-specific announcements is currently of interest in the literature; primarily based on a recent stream of literature suggest that short sellers are no more sophisticated prior to information events than other traders (Daske etal. 2005; Boehmer and Wu, 2008; Chakrabarty and Shkilko, 2008; Blau and Wade, 2011; Blau and Pinegar, 2010). These studies bring into question the sophistication and informativeness of short sellers prior to negative news events.

The opaqueness of financial institutions, such as insurance companies, banks, and investment funds, has been the topic research examining information related factors and information asymmetries between financial institutions and investors. Ross (1989) compares the opaqueness of banks, insurance companies, and mutual funds and suggests that banks and insurers contain more asymmetric information in their asset composition than mutual funds. Additionally, Ross (1989) interprets the results as insurance companies and banks are among the most opaque because managers have informational advantages about firm operations and specifically, the level of risk in the firm's asset structure. Flannery, Kwan, and Nimalendran, (2004) examined the relative opaqueness of various assets in bank portfolios and showed that asset opaqueness affected the adverse selection costs. Overall, the literature suggests that insurance companies and banks present the greatest degree of information asymmetry between claimholders and the financial institution in regards to the institutions assets (Polonchek and Miller, 1996).

However there are differences in opaqueness between banks and insurance companies. While both banks and insurance companies have a relatively similar asset opaqueness structure, their liability structures differ significantly. Banks' liabilities are normally well-classified in regards to the monetary sum and length of exposure. However, insurance companies are unique in this manner, since their liabilities are far less certain due to the predictability of the length of the claims payout and the final overall payout. As such the insurers' liabilities create a much larger degree of information asymmetry than that of a bank. Specifically, there exists uncertainty about the payout on claims between some lines of business, which increases the information asymmetry between claimholders, investors and the financial institution.

Specific to insurers, the liabilities are defined within the property-casualty (P/C) and life-health (L/H) lines. Babbel and Merrill (2005) suggest the intricate nature and opaqueness of insurance policies allow managers for both P/C and L/H insurers to generate ambiguous financial measures of liabilities, surplus, and reserves. Phillips, Cummins, and Allen (1998) separate P/C lines of business into long-tailed and short-tailed lines, depending on the length of the claim payouts. Their results show the price of insurance is inversely related to the riskiness of the firm, and that this is stronger for long-tail lines of business than for short-tail lines. Colquitt, Hoyt, and McCullough (2006) indicate P/C insurers increase the information asymmetry by utilizing greater discretion in setting loss reserves.

In examining life/health insurers, Baranoff and Sager (2002) suggest that accident and health lines contain more asymmetric information than annuities because of the uncertainty of when claims will be paid out. Baranoff and Sager (2002) also suggest that group lines of business contain more asymmetric information than individual lines. Zhang et al. (2009) separate lines of business into opaque and transparent lines. The authors then test the effects of opaqueness on the adverse selection component of the bid-ask spread. Their findings suggest that the opaqueness of a firm's liabilities directly affects the adverse selection component of the spread.

These multiple streams of literature; the information content in IFSR, the informativeness and sophistication of short sellers, and the understanding that insurance companies vary in their degree of information asymmetry, lead us to develop two hypotheses presented in the following section.

CHAPTER 2.3

HYPOTHESES DEVELOPMENT

Ratings of publicly traded insurers come in a number of forms and provide investors an indication of a myriad of firm risk characteristics such as investment risk, credit risk, default risk, insolvency risk and financial strength. With the recent financial crisis and the concerns around insolvency of financial institutions, the importance for accurate and timely information regarding the insolvency risk of insurers is evident. With that, insurer financial strength ratings (IFSR), which are one form of ratings of public insurers, historically has provided information on insolvency risk to potential investors, as well as insight to consumers of insurance products. Halek and Eckles (2010) indicate that through the diligence of the ratings process and working relationship between rating analysts and insurance company management, rating analysts may have more information regarding an insurer than the investing public, providing rating announcements with potential informational value for capital markets. Our research extends Halek and Eckles (2010) and examines the response of informed traders to the potential contribution of the enhanced information content to the market provided by changes in IFSR.

Should the information conveyed in IFSR changes provide information to the market, one would expect informed traders would be able to capitalize on this superior information. This would be particularly evident in ratings downgrades, which have been accepted in the literature as a negative news event. Some research indicates short sellers are active traders who capitalize on superior information about future stock performance and the true value of stocks (Diamond and Verrecchia, 1987). Further, empirical results indicate that short selling is inversely related to subsequent returns and that this relationship is particularly evident in informational rich events with unfavorable announcements (Senchack and Starks, 1993; Aitken et al. 1998; Desai et al. 2002; Boehmer et al. 2008; Engelberg et al. 2010; Christophe et al. 2004; Christophe et al. 2010). However, others question the informativeness of short sellers prior to negative news events and suggest short sellers are no more sophisticated prior to information events than other traders (Daske et al. 2005; Boehmer and Wu, 2008; Blau and Wade, 2011; Blau and Pinegar, 2010).

Motivated by these conflicting viewpoints, our study examines short selling around IFSR changes. Insurer financial strength rating (IFSR) downgrades make tests of informed short selling relevant for two reasons. First, IFSR announcements are not scheduled; as such the announcement is less predictable than other types of announcements. Secondly, IFSR are focused on insurance companies who vary in their level of opaqueness (Ross, 1989; Baranoff and Sager, 2002; Zhang et al. 2009). The opaqueness of the liability and asset structure of an insurer may challenge short sellers' information processing ability based on uncertainty of claims payouts. Thus, IFSR changes provide a robust framework for testing whether short sellers have a superior ability to process information or are privately informed. If short sellers are either privately informed or better able to process the information contained in IFSR, we expect to see abnormally high short selling before IFSR downgrades, regardless of the degree of opaqueness in the insurers asset and liability structure. Together we propose two hypotheses: *sophisticated trading* hypothesis and the *front running* hypothesis.

The sophistication of short sellers is empirically supported by numerous studies that find short selling is inversely related to subsequent returns (Senchack and Starks, 1993; Aitken et al. 1998; Desai et al. 2002; Boehmer et al. 2008; Engelberg et al. 2010; Christophe et al. 2004;

Christophe et al. 2010). Most recently, Christophe et al. (2004) and Christophe et al. (2010) examine shorting activity prior to earnings announcements and analyst recommendations, respectively, and find that short selling is abnormally high prior to both unfavorable earnings announcements and downward analyst recommendation changes. Based on these finding that short sellers have a remarkable ability to capitalize on negative news events, we hypothesis the following:

Hypothesis 1- There will be abnormal short selling in the insurer stock prior to the IFSR downgrade (sophisticated trading hypothesis).

The alternative to *Hypothesis 1* is that the IFSR downgrade announcement will have a positive (or no) effect on short selling. Observing normal levels of shorting activity during the IFSR pre-announcement period indicates that either (i) short sellers are caught off guard by the IFSR announcement or (ii) short sellers are unable to obtain private information during the IFSR pre-announcement period.

Following *Hypothesis 1*, we examine the effect opaqueness in insurer's lines of business or assets have on short selling around ratings downgrades. It has been argued that the insurance industry is more opaque that other industries (Morgan, 2002). Insurance firms vary in their level of opaqueness as their liability structure is focused in different lines of insurance business that vary in the level of uncertainty (Zhang et al., 2009). In a general sense opaqueness may have an adverse affect on information processing due to the difficulty of obtaining information for more opaque stocks. However should short sellers be sophisticated or privately informed, the level of opaqueness should not have a negative impact on the short selling activity. As such, taking these findings coupled with the findings suggesting short sellers are privately informed or sophisticated in their ability to process information, we hypothesize the following:

Hypothesis 2 – The opaqueness of a firm's liabilities will positively affect the level of short selling in the insurer stock prior to the IFSR downgrade (front running hypothesis).

The alternative to *Hypothesis 2* is that opaqueness will have a negative effect on short selling. It has been argued that should short sellers are not privately informed nor overly sophisticated in their processing of information prior to information compared to other traders (Daske et al. 2005; Boehmer and Wu, 2008; Chakrabarty and Shkilko, 2008; Blau and Wade, 2011; Blau and Pinegar, 2010).

We expect evaluating these hypotheses will yield a better understating of how the information conveyed in IFSR downgrades is incorporated by short sellers and if opaqueness in the firms lines of business or assets impacts short selling around IFSR downgrades.

CHAPTER 2.4

SAMPLE AND DATA

A.M. Best's Key Rating Guides and A.M. Best's Insurance Reports provide insurer ratings data for our sample period January 1, 2005 to December 31, 2006. In defining our ratings sample, we follow the methodology of Halek and Eckles (2010). Insurers in our sample must be rated twice during the 2005-2006 sample period. Based on the nature of the insurance industry, frequently multiple individual insurance companies may be held by a single publicly traded company. In these instances, the group rating for an insurer is utilized; while sole companies that are not a member (or a singular member) of a group, the rating for that single company is used. Furthermore, if there is not a group rating for a publicly traded insurer, but companies within the group have similar ratings, this similar rating is used.

The sample consists of 25 publicly traded insurers (14-PC, 11-LH) with a total of 25 A.M. Best ratings downgrades. While we would prefer to analyze more events, we are restricted in the extending our time period because Regulation SHO data was not available before 2005 and after the first of 2007. It should be noted, over our 2 year time period the distribution of ratings events is consistent with previous annual ratings events over a 10 year period (Halek and Eckles, 2010). In addition, we focus or analysis on A.M. Best ratings, as previous work has suggested event study results vary by the rating agency making the announcement, where A.M. Best provide stronger results when reporting cumulative abnormal returns around announcements when compared to those of S&P or Moody's (Halek and Eckles, 2010; Halek and Eckles, 2011).

Several restrictions are placed on our data in arriving at our final sample. Ratings are eliminated if they occur within 5-days of an S&P, Moody's or Weiss ratings change. Halek and Eckles (2011) present the reinforcement hypothesis, suggesting the market reaction is likely to be more severe when capturing the effect of a rating issued in possible response to another rating. Further ratings were eliminated if the insurer rating downgrade was due to other announcements or events directly related to the insurer that occurred around the time of the downgrade (Halek and Eckles, 2011). For example, our sample is during the hurricane seasons of 2005 and 2006. If a rating agency downgraded an insurer because of "weather related influences" on the same or previous day, any associated decline in stock returns may be a result of the response to the hurricane landfall rather the downgrade itself. As such we eliminate ratings within 5-days of identified "related" events.

We obtain short sale data in response to the Regulation SHO. From the Center of Research on Security Prices (CRSP), we obtain daily volume, prices, returns, shares outstanding, and market capitalization. After aggregating the short sale data to the daily level, we calculate a measure that is frequently used in the literature (Boehmer and Wu, 2008; Diether et al. 2009; Blau and Wade, 2011). Following Diether et al. (2009), we restrict our sample to stocks that trade every day of the time period (January 2005 to December 2006); have price greater than $2; and have a CRSP share code of 10 or 11). We obtain the lines of business, liability and asset data from the NAIC database and follow Zhang et al. (2009) and Baranoff and Sager (2003) in defining opaque and non-opaque liabilities and assets in P/C, and L/H lines of business, respectively.

Testing the *sophisticated trading and front running* hypotheses, we examine short selling prior to IFSR downgrades, as well as the relation between abnormal short selling and the degree of opaqueness of downgraded insurers. In testing these hypotheses we follow previous literature in defining the dependent and independent control variables. The following section documents the variables.

Dependent Variables

Short Ratio: Deither et al (2009) defined the short ratio, as the daily number of shares sold short for a stock day divided by the total number of shares traded in the stock during the same day, to normalize across stocks. The authors suggested the short ratio measure is much less skewed than the other measures of short-selling activity. Further Christophe et al. (2010) suggested that distributional differences in short selling activity around announcement events may be due to unusually high or low trading volume prior to the announcement, and by measuring short selling as a percentage of trading volume would result in a relatively constant measure. We calculate the short ratio (*SR*) as the daily number of shares sold short for a stock day divided by the total number of shares traded in the stock during the same day.

Short Turnover: There are variations in the literature as to which measure of short selling is used in empirical testing. For instance, recent event studies by Chakrabarty and Shkilko (2010), Christophe et al. (2010), and Massoud et al. (2010) break from the short ratio methodology used in some of the prior studies (Diether et al., 2009), and use an alternative methods to scale short volume (short turnover). Chakrabarty and Shkilko (2010) use the natural log adjustment of short volume simultaneously controlling for non-short volume in their regression models. Christophe et al. (2010) scale short volume by the number of shares outstanding, whereas Massoud et al. (2010) scale short volume by its historical average. Consistent with these studies we calculate the daily short turnover (*STO)* as the daily short volume scaled by the number of shares outstanding;

Independent Variables

Size: Diether et al. (2009) and Boehmer et al. (2007) report that market capitalization influences the short selling of stocks. The authors suggest smaller stocks may have less of a following by analysts and therefore, may experience more trading by informed investors than larger stocks. Additionally, Arnold et al. (2005) use market capitalization as a proxy for institutional holdings, suggesting that institutions are likely to hold larger cap stocks. Therefore, a security's market capitalization will affect the level of short selling. However, if asymmetric information exists more in small-cap stocks, then short selling may be negatively related to size. Consistent with this argument, Diether et al. (2009) find that short sellers are more informed in smaller stocks. They also document a positive relation between trading activity and the level of short selling.

Past Returns: Diether et al. (2009) show that daily short volume is positively related to lagged returns. Our variable $ret_{i,t-3t-1}$, represents the movement of the stock price during the three days prior to the A.M. Best ratings change announcement. This variable controls for the possibility that upward or downward changes in the stock price might affect the level of short-selling in the days leading up to the announcement. A pre-announcement increase in stock price, for example, might affect short-selling by inducing some investors to short the now "over-valued" stock. With this control variable in place, the model does not wrongly attribute all pre-announcement short-selling to expectations regarding the earnings release.

Price Volatility: Following Diether et al. (2009), price volatility is calculated by taking the difference between the daily high price and the daily low price (both from CRSP) and dividing the difference by the daily high price. Diether et al. (2009) document that price volatility positively affects the level of short selling. If short sellers are informed, as the literature suggests, then the level of short selling will be a function of the flow of information into the market. Clark (1973) and Lamoureux and Lastrapes (1990) establish a theoretical relation between price volatility and information flow.

Return Volatility: Avramov, Chordia, and Goyal (2006), studied the impact of trades on daily volatility. They find that increased activity by contrarian traders (identified as sales following price increases) is associated with lower future volatility, while increased activity by herding investors (identified as buyers after price increases) is associated with higher future volatility. Avramov et al. (2006) argue that contrarian traders are rational traders who trade to benefit from the deviation of prices from fundamentals. As these trades make prices more informative, they tend to reduce future return volatility.

Lagged Short Selling: Short selling and trading volume are both positively autocorrelated (Blau et al, 2008; Blau 2010). To account for this, we include lagged short sales ($SSR_{,t-8,t-4;}$ $SSTO_{,t-8,t-4}$) and turnover ($vto_{i,t-3,t-}$) on the right-hand side. If returns are positively autocorrelated, we risk falsely associating past returns with today's short-selling activity. Therefore, we also include the contemporaneous return ($ret_{i,t-3t-1}$) as an explanatory variable.

Down: The variable of interest is the indicator variable *Down*, which equals one if day *t* is the day of a ratings downgrade; zero otherwise. If short sellers can anticipate unfavorable ratings changes, then we expect the estimate for *Down* to be significantly positive.

Up: The variable of interest in our robustness test is the indicator variable *Up*, which equals one if day *t* is the day of a ratings upgrade; zero otherwise.

Opaqueness: We follow Zhang et al. (2009) and Baranoff and Sager (2003) in defining opaque and non-opaque lines of business and assets in P/C, and L/H lines of business, respectively. PCopaque is the ratio of premiums written in opaque PC lines of business relative to total premiums written in PC lines. LHopaque is the percentage of premiums written in opaque LH lines of business relative to premiums written in LH lines. We combine these measures and arrive at a measure Lopaque defined as the percentage of premiums written in all opaque lines of business relative to total premiums. We follow Flannery et al. (2004) and Zhang et al. (2009) methodologies to define the asset opaqueness measure Aopaque. By the Aopaque definition the most opaque assets held by an insurer are: mortgage loans, real estate investment, private placement loans and bonds, premium notes, premiums receivable, other investments, reinsurance recoverable on loss and loss adjustment expense payments and reinsurance ceded.

Table 1 presents statistics that describe our sample. Panel A of Table 1 reports the downgraded firm characteristics during the entire sample time period, while Panel B. reports the downgraded firm characteristics on downgrade day. Panel A shows that the average stock in our sample has a price of $37.41, a market capitalization of $12.2 billion, a return volatility of 1.5

percent, and price volatility of 2.2 percent. Turnover, which is the daily trade volume divided by the number of shares outstanding is the .49 percent. The mean short ratio is 18.04 percent, which suggests that, on average, approximately 18 percent of daily trade volume is made up from short sales. This figure is consistent with findings in Diether et al., (2009) and Blau et al., (2008). Panel B shows that firms in the sample on the downgrade date has a price of $41.27 with a negative return of -0.0128. It should be noted that on the downgrade day the short ratio increased to 27% of trading volume.

CHAPTER 2.5

EMPIRICAL METHODOLOGY

We test the impact of ratings downgrades using both univariate and multivariate tests. We also test the relation of short selling and the degree of opaqueness in insurers' liabilities and assets around ratings downgrades. We conduct a standard event study using an 8-day window around rating downgrades. We report market adjusted returns, which are calculated using the daily (CRSP) raw returns less the equally-weighted CRSP index return. We compute the average market adjusted returns for each and run a (cross-sectional) pair-wise *t*-test of changes in the mean.

Our univariate short selling event study methodology follows several studies that examine trading activity around particular events (Lakonishok and Vermaelen, 1986; Koski and Scruggs, 1998; and Sias, 2004) using the following equation:

$$standardized\ short\ sell_{i,t} = \frac{short\ sell_{i,t} - \overline{short\ sell_i}}{\sigma(short\ sell_i)} \qquad (1)$$

Specifically, we divide the difference between (i) the trading activity measure on day *t* for each stock *i* and (ii) the sample period mean of this measure for this stock by (iii) the sample period standard deviation for the stock. The procedure allows for a standardized measure that is similarly distributed across stocks, with a zero mean and a unit variance. This standardization makes shorting activity comparable across stocks with different trading volume. If more shorting systematically contributes to greater price efficiency, stock prices should deviate less from a random walk (Boehmer et al. 2008). Similar to the market adjusted returns analysis, we compute the average standardized short ratio and standardized short turnover for each and run a (cross-sectional) pair-wise *t*-test of changes in the mean.

Our multivariate analysis is performed with panel data models examining both stock and day effects. We used a Hausman specification test to compare the fixed versus random effects under the null hypothesis that the individual effects are uncorrelated with the other regressors in the model (Hausman 1978). H_0 was rejected; as such a random effect model would produce biased estimators. As a result we estimate equation (2 and 3) while controlling for both stock and day fixed effects. Qualitatively similar results are obtained when we estimate standard errors that cluster by both stock and day (Thompson, 2006). Recognizing the need to control for other factors that influence the level of short-selling activity, we therefore estimate the following equations using the panel data fixed effect model:

$$SSR_{i,\,t-3,t-1} = \beta_0 + \beta_1 size_{i,t} + \beta_2 ret_{i,t-3t-1} + \beta_3 vto_{i,t-3,t-1} + \beta_4 p\_volt_{i,t-3,t-1} + \beta_5 r\_volt_{i,t-3,t-1} + \beta_6 SSR_{,t-8,t-4} + \beta_7 Down_t + \varepsilon_{i,t-3,t-1} \quad (2)$$

$$SSTO_{i,\,t-3,t-1} = \beta_0 + \beta_1 size_{i,t} + \beta_2 ret_{i,t-3t-1} + \beta_3 vto_{i,t-3,t-1} + \beta_4 p\_volt_{i,t-3,t-1} + \beta_5 r\_volt_{i,t-3,t-1} + \beta_6 SSTO_{i,t-8,t-4} + \beta_7 Down_t + \varepsilon_{i,t-3,t-1} \quad (3)$$

The dependent variable is the short selling measure (SSR-standardized short ratio or SSTO-standardized short turnover) from days *t-3* to *t-1*. Following Diether et al. (2009) we include turnover ($turn_{i,t-3,t-1}$), price volatility ($p\_volt_{i,t-3,t-1}$), return volatility ($r\_volt_{i,t-3,t-1}$), and contemporaneous market-adjusted returns ($ret_{i,t-3,t-1}$). As mentioned previously, Diether et al.

(2009) find that short selling is contrarian; to control for the contrarian behavior of short sellers, we include the cumulative contemporaneous return ($ret_{i,t-3,t-1}$). A lagged dependent variable ($SSR_{,t-8,t-4}$ *and* $SSTO_{,t-8,t-4}$ *and*) is also included to control for serial correlation in short-sale volume. The variables of interest include the indicator variable *Down*, which equals one if day *t* is the day of a ratings downgrade; zero otherwise. If short sellers can anticipate unfavorable ratings changes, then we expect the estimate for *Down* to be significantly positive.

It has been argued that the insurance industry is more opaque that other industries (Morgan, 2002). In addition, insurance firms vary in their level of opaqueness as their liability and asset structure, while focusing in different lines of insurance business that vary in the level of uncertainty (Zhang et al., 2009). In testing the *front running* hypothesis, we further extend our regression analysis by examining the relation between abnormal short selling and the degree of opaqueness of downgraded insurers, as follows:

$$SSR_{i,t-3,t-1} = \beta_0 + \beta_1 size_{i,t} + \beta_2 ret_{i,t-3t-1} + \beta_3 vto_{i,t-3,t-1} + \beta_4 p\_volt_{i,t-3,t-1} + \beta_5 r\_volt_{i,t-3,t-1} + \beta_6 Sh\_sell_{,t-8,t-4} + \beta_7 Down_t + \beta_8 Lopaque_t + \beta_9 Aopaque + \beta_{10} Down_t \, x \, Lopaque_t + \beta_{11} Down_t \, x \, Aopaque_t + \varepsilon_{i,t-3,t-1} \quad (4)$$

$$SSTO_{i,t-3,t-1} = \beta_0 + \beta_1 size_{i,t} + \beta_2 ret_{i,t-3t-1} + \beta_3 vto_{i,t-3,t-1} + \beta_4 p\_volt_{i,t-3,t-1} + \beta_5 r\_volt_{i,t-3,t-1} + \beta_6 Sh\_sell_{,t-8,t-4} + \beta_7 Down_t + \beta_8 Lopaque_t + \beta_9 Aopaque + \beta_{10} Down_t \, x \, Lopaque_t + \beta_{11} Down_t \, x \, Aopaque_t + \varepsilon_{i,t-3,t-1} \quad (5)$$

Similar to equations 2 and 3 we estimate equations 4 and 5 while controlling for both stock and day fixed effects. Qualitatively similar results are obtained when we estimate standard errors that cluster by both stock and day (Thompson, 2006). The variables specifications are the same as in equation 2 and 3, while we include the opaqueness measures for both liabilities (*Lopaque*) and assets (*Aopaque*) following Zhang et al. (2009) and Baranoff and Sager (2003). Again, the variables of interest include the indicator variable *Down,* which equals one if day *t* is the day of a ratings downgrade; zero otherwise. We also interact the opaqueness variables and the dummy variable ($Lopaque_t \times Down_t$; $Aopaque_t \times Down_t$) to determine the relation of the degree of opaqueness of the firm's liabilities or assets to short selling around IFSR downgrades.

For robustness in addressing the findings of Christophe et al. (2010) and Blau and Wade (2011), we follow Blau and Wade (2011) and examine short selling around favorable IFSR changes. The univariate analysis and variable specifications are identical to that of the IFSR downgrade analysis, with the exception of the indicator variable *Up*, which equals one if day *t* is the day of a ratings upgrade; zero otherwise. Our multivariate panel regression analysis for upgrades follows that of the downgrade analysis by estimating the following equations:

$$SSR_{i\,t} = \beta_0 + \beta_1 size_{i,t} + \beta_2 ret_{i,t} + \beta_3 vto_{i,t-3,t-1} + \beta_4 p\_volt_{i,t-3,t-1} + \beta_5 UP_t + \varepsilon_{i,t-5,t-1} \quad (6)$$

$$SSTO_{i\,t} = \beta_0 + \beta_1 size_{i,t} + \beta_2 ret_{i,t} + \beta_3 vto_{i,t-3,t-1} + \beta_4 p\_volt_{i,t-3,t-1} + \beta_5 UP_t + \varepsilon_{i,t-5,t-1} \quad (7)$$

CHAPTER 2.6

RESULTS

We begin our analysis by examining downgrades using both univariate and multivariate tests. We also test the relation the opaqueness in insurer's lines of business or assets to short selling around IFSR downgrades.

Short Selling around Downgrades

Our motivation for the current study is the conflicting findings around short sellers and their ability to capitalize on negative news announcements, combined with those of Halek and Eckles (2010) indicating insurer financial strength ratings provide informational value to the market, specifically that of unfavorable ratings.

Table 2 presents the distribution of ratings over the sample period. Table 3 contains the results of a standard event study using an 8-day window around rating downgrades. Column (1) shows market-adjusted returns, which are calculated using the daily (CRSP) raw returns less the equally-weighted CRSP index return. Consistent with Halek and Eckles (2010), we find that returns begin to adjust in the two days prior to the ratings downgrade. As expected, daily returns are significantly negative on the event day and continue to remain negative for three days after the downgrade. These results suggest that (i) observed downgrades negatively affect the company's stock price and (ii) the stock price begins to adjust before the ratings change is publicly observed. The implication that the stock price begins to adjust before the ratings change is publicly observed, suggests that some investors either predict the downgrade or somehow acquire private information that the ratings will be revised downward. In columns (2) through (5), we examine the short selling surrounding downgrades. In column (2 and 4), we report the short ratio and short turnover.

The results in columns (2) through (5) show that short selling begin to increase a day prior to downgrades for both short selling standardized measures. These initial univariate results affirmatively answer the question that short sellers can anticipate unfavorable ratings changes, lending initial support in favor of the *sophisticated trading* hypothesis. A possible explanation for these findings is that short sellers are sophisticated in processing information about the upcoming ratings change prior to the public disclosure. Irvine et al. (2007) argue that abnormal institutional trading activity prior to initial analyst recommendations is consistent with the tipping hypothesis. The tipping hypothesis suggests that analysts are inclined to tip preferred or potential clients because it allows for short-term trading profits. While we do not go as far to say that ratings agencies are the source of information leakages, we do note that observing abnormal short selling prior to ratings downgrades are consistent with private information.

The aforementioned argument against the interpretation of our findings suggests that short sellers are trading on the same information that ratings agencies use to conduct their analysis and make their ratings of financial strength. On day *t-1*, both standardized short selling measures are larger than on any other day in the pre-downgrade period. Ratings agencies have likely conducted the analysis before day *t-1*, so observing the highest amount of short selling the day before the ratings downgrade during the pre-downgrade period provides us with further confidence that short sellers have acquired private information about the upcoming ratings change before the information has become publicly available. Table 3 also shows that the short selling spikes on day t and is abnormally high on the day after the downgrade. These results suggest that short sellers attenuate the downward price response documented in Halek and Eckles (2010).

Table 4 columns [1] and [2] report the regression results using standardized short ratio and standardized short turnover, as the dependent variable, respectively. We find turnover, price volatility, and lagged shorting activity are positively related to short selling. Similar to Diether et al. (2009), we also find short sellers are contrarian in contemporaneous returns as the estimate for β_1 is significantly positive. Further, we still observe standardized short selling during the eight days prior to ratings downgrade to be positive.

The results in Tables 3 and 4 suggest that short sellers are able to successfully anticipate ratings downgrades as we find abnormal short selling of insurance stocks on the day prior to a ratings downgrade. Further, the results in Tables 3 and 4 lead us to accept the *sophisticated trading* hypothesis. A possible explanation is that information about the upcoming ratings downgrade leaks to market participants prior to downgrades. Because information leaks are not observed, our explanation is left open to criticism. While, short selling prior to unfavorable ratings changes is, at a minimum, consistent with what we would expect to see if information was leaking into the market; we are left to interpret our results as short sellers are sophisticated traders specifically around IFSR rating.

As mentioned earlier, we focus our attention on the effect of the opaque variables. Table 5 presents the descriptive statistics for the opaqueness measures calculated following Zhang et al. (2009) and Baranoff and Sager (2003). Table 6 presents the results for equations 4 and 5. We find that the coefficient estimates for *Lopaque,* and *Aopaque,* are significantly negative in both dependent variable specifications. We interpret these results to indicate that firm opaqueness in liabilities and assets negatively affects the level of short selling activity. However, this result does not lead us to reject the *front running* hypothesis as it stands. We turn our attention to the indicator variable *Down*, which equals one if day *t* is the day of a ratings downgrade; zero otherwise. We report a significant positive coefficient for the *Down* dummy when controlling for the opaque variables for each dependent variable specification. We interpret these results as evidence that short sellers can anticipate unfavorable ratings changes, which is consistent with the *sophisticated trading* hypothesis. The findings of interest are the interaction effects which directly tests the *front running* hypothesis. We interact the opaqueness variables and the dummy variable ($Lopaque_t \times Down_t$; $Aopaque_t \times Down_t$) to determine the relation of the degree of opaqueness of the firm's liabilities or assets to short selling around an IFSR downgrade. The results indicate negative and significant findings for insurers around downgrades. We interpret these results as short sellers are not any better at predicting future negative returns around IFRS downgrades of insurers with a higher degree of opaqueness, but rather the short selling around IFRS downgrades is primarily focused in lower opaque insurance firms. This interaction effect leads us to reject the *front running* hypothesis and suggest that while short sellers are indeed sophisticated traders they are not necessarily privately informed around IFSR downgrades

Robustness: Short Selling around Upgrades

In this subsection, we examine short selling around upgrades as a measure of robustness in testing whether short sellers can successfully anticipate ratings changes. We show abnormal short selling prior to ratings downgrades. Here, we expect that short selling will be abnormally low prior ratings upgrades.

Table 7 contains the results of an event study around upgrades that mirrors the methods used around downgrades (Table 3). Again, we focus our study on market-adjusted returns and short selling surrounding upgrades. In column (1), we see that market-adjusted returns positively react to upgrades as returns are positive and significant on day *t*. Compared to the results in Table 3, the return reaction for upgrades (0.0102) is less than half in magnitude than the return reaction for downgrades (-0.0128). This finding is consistent with the conclusion in (Halek and Eckles, 2010), who argue that prices respond more to downgrades than to upgrades. Further, we find the prices begin to react the day before the upgrade as market-adjusted returns are 0.0035 on day *t-1*. We now turn our focus to our short selling measures. The standardized short ratio is obtained using equation (1). As expected, we find abnormally low short selling in the eight days prior to upgrades. However, we observe a striking result on day *t* as short selling significantly spikes and remains positive on day *t+1*. We interpret this latter result as consistency with the notion that short sellers add to the informational efficiency in prices (Boehmer and Wu, 2008). Diether et al. (2009) submit that short sellers target stocks that become overvalued. This new finding of abnormal short selling on days with positive news suggests that short sellers are attenuating the price efficiency of stocks by monitoring the price reaction to the news of an upgrade.

In columns (1 and 2) of Table 8, we find that after controlling for some of the factors that influence the level of short selling, we observe abnormal short selling on days with upgrades. Interestingly, in columns (1) and (2), the estimate for the dummy variable *UP* is significantly negative. A possible explanation is that short sellers are not concerned with the announcement as much as they are concerned with the price reaction to the announcements. This interpretation is consistent with Diether et al. (2009), who argue that short sellers target stocks that become out of line with their fundamental value. The findings in Tables 7 and 8 suggest that short sellers, who are known to add to the informational efficiency of prices (Boehmer and Wu, 2008), believe that stocks become overvalued in response to ratings upgrades.

Tests of whether stocks become mispriced in response to upgrades are outside the scope of this paper. However, Halek and Eckles (2010) conclude that prices have little or no response to good news in ratings in the form of upgrades suggesting that upgrades do not contain a lot of informational value to the market. Our findings, at a minimum, suggest that some short sellers believe that little or no information is contained in upgrades. Relative to the results in Halek and Eckles (2010), our study suggests that part of the reason prices do not substantially respond to upgrades is because some pessimistic investors do not feel ratings upgrades provide any informational value. Continued analysis of this conjecture is left to further research. The findings in Table 7 and 8 indicate that (i) abnormally low short selling occurs before upgrades supporting earlier findings that imply short sellers anticipate ratings changes and (ii) short selling surges on days with favorable ratings changes suggesting that short sellers do not believe that upgrades contain informational value about future returns.

CHAPTER 2.7

CONCLUSIONS

The results of this study indicate that short sellers successfully anticipate ratings changes as short selling is abnormally high (low) prior to ratings downgrades (upgrades). These findings help explain the results in Halek and Eckles (2010), who show that prices adjust to unfavorable ratings changes while positive ratings changes have little or no effect on price movements. Combined with Halek and Eckles (2010) results, we show that short selling attenuates the downside price pressure in response to downgrades. Further, our study suggests that a partial reason that prices do not substantially react to upgrades is because some short sellers do not believe that upgrades contain informational value to market participants.

While others show that short selling can predict negative returns at the daily level, we show that the negative relation between current short selling and future returns is stronger on the day before downgrades. Further, after controlling for other factors that influence future returns, we show that short selling on days with favorable ratings changes can predict negative returns better than usual. We recognize that information leakages are not observed and so the interpretation of our tests is left to some criticism. However, abnormal short selling prior to downgrades is at a minimum, consistent with the notion that information about upcoming ratings changes is absorbed to short sellers prior to the public dissemination of the ratings changes.

The results of this analysis provide initial evidence supporting the idea that information about upcoming ratings changes is available to short sellers, particularly for negative news events such as ratings downgrades. For positive news events, we document new evidence supporting the notion that short sellers target stocks they believe have become overvalued. While we do not test whether insurance stocks are mispriced after upgrades, we provide an indication that some investors believe that indeed they are. While we find abnormal short selling prior to ratings downgrades, we also find that an insurers' asset and liability opaqueness negatively affects the level of short selling activity prior to a financial strength ratings downgrade. We are left to conclude that while short sellers are superior in their information processing ability, they do not appear to be privately informed around insurer financial strength ratings changes. A fruitful area of future research may be to determine the price efficiency of insurance stocks around insurer financial strength ratings.

Table 1
Summary Statistics
The table shows summary statistics of the sample used in the analysis. Panel A reports the price, market adjusted returns, market capitalization, the return volatility, the price volatility, the share turnover, the short turnover, and the short ratio for the average stock used in our sample. *Size* is the CRSP market capitalization. *R_volt* is the return volatility calculated as the standard deviation of the daily returns from day *t-10* to day *t*, where day *t* is the current trading day. *P_volt* is the price volatility obtained by taking the difference between the daily high price and the daily low price divided by the daily high price. *Turnover* is the trade volume divided by the shares outstanding while the *short turnover (sto)* is the short volume divided by the shares outstanding. *Short ratio* is the short volume divided by the total volume.

Panel A. Downgraded firm characteristics during the entire sample time period.

	N	Mean	Median	Min	Max
Price	25	37.4100	32.3559	2.2415	107.8710
Return	25	0.0007	0.0006	-0.0002	0.0019
Size	25	12,260,546	1,057,706	57,010	164,459,426
Rvolt	25	0.0154	0.0152	0.0040	0.0252
Pvolt	25	0.0228	0.0226	0.0089	0.0355
Vto	25	0.0049	0.0042	0.0003	0.0126
Sto	25	0.0019	0.0018	0.0001	0.0033
Short Ratio	25	0.1804	0.1856	0.0380	0.2678

Panel B. Downgraded firm characteristics on downgrade day.

	N	Mean	Median	Min	Max
Price	25	41.2719	38.6650	2.4000	129.6600
Return	25	-0.0128	-0.0099	-0.0733	0.0326
Size	25	12,585,986	1,240,915	50,066	145,815,268
Rvolt	25	0.0166	0.0160	0.0059	0.0341
Pvolt	25	0.1571	0.1328	0.0702	0.7363
Vto	25	0.0057	0.0039	0.0001	0.0356
Sto	25	0.0092	0.0087	0.0020	0.0163
Short Ratio	25	0.2752	0.2450	0.0001	0.5340

Table 2. A.M. Best ratings downgrades between 2005-2006.

All Downgrades during the sample time period.

	2005		2006	
	PC-Group	LH-Group	PC-Group	LH-Group
Jan				1
Feb				
Mar			2	
Apr	3			1
May	1	1	3	
Jun			1	
Jul				1
Aug			1	
Sep	1		1	
Oct	1	1	1	
Nov	4			2
Dec	1	3	3	1
Year Total	11	5	12	6
Sample Total	**34**			

Current sample of Downgrades used in analysis

	2005		2006	
2005	PC-Group	LH-Group	PC-Group	LH-Group
Jan				1
Feb				
Mar			1	
Apr	1			1
May	1	1	2	
Jun			1	
Jul				1
Aug			1	
Sep	1		1	
Oct	1	1	1	
Nov	4			1
Dec	1	1	1	1
Year Total	9	3	8	5
Sample Total	**25**			

Table 3
Short Selling around A.M. Best Rating Downgrades
The table shows a standard event study of market-adjusted returns and short selling around A.M. Best rating downgrades. We obtain downgrades from A.M. Best data and report the market-adjusted returns (the difference between the daily return and the CRSP equally-weighted return for a particular stock), the short ratio, and the short turnover surrounding rating downgrades. Tests for significant returns are determined by standard *t*-statistics testing for differences from zero. We test for the significance in short selling using two different methods. We also standardize short selling activity by calculating the difference between the short activity for stock *i* on day *t* and the mean short activity for stock *i* (across the sample time period). We then divide the difference by the standard deviation of daily short activity so that each short measure on each day is similarly distributed with a zero mea n and a unit variance. *T*-statistics testing whether the standardized measure is significantly different than zero (the mean) are obtain. Results from *t*-tests, which test whether the standardized and abnormal measures are significantly different than zero (the mean) are shown using asterisks.

	Adjusted Returns	Short Ratio	Std_Short Ratio	Short Turnover	Std_SShort Turnover
	[1]	[2]	[3]	[4]	[5]
t-8,t-4	0.0093*	0.2031	0.3977**	0.0008	0.2212
t-3	-0.0036	0.2332	0.3291	0.0006	0.0793
t-2	-0.0109**	0.2106	0.3944	0.0006	0.0963
t-1	-0.0121**	0.2412	0.5122**	0.0054	0.2915**
event day	-0.0128**	0.2752	0.6612**	0.0092	0.5009**
t+1	-0.0039*	0.2062	0.2433	0.0063	0.3764**
t+2	-0.0071**	0.2069	0.1293	0.001	0.1534
t+3	-0.005	0.1999	0.1857	0.0042	0.1692
t+4,t+8	0.0009	0.1855	0.3012	0.0017	0.0154

Table 4
Panel Regression Results
The table presents the panel regression results from estimating the following equation where the dependent variable is short-selling activity from day *t-3* to *t-1*. Short selling specifications are the standardized short ratio ($Ssr_{i,\ t\text{-}3\ t\text{-}1}$) and standardized short turnover ($Ssto_{i,\ t\text{-}3\ t\text{-}1}$).

$$SSR_{i,\ t-3,t-1} = \beta_0 + \beta_1 size_{i,t} + \beta_2 ret_{i,t-3t-1} + \beta_3 vto_{i,t-3,t-1} + \beta_4 p\_volt_{i,t-3,t-1} + \beta_5 r\_volt_{i,t-3,t-1} + \beta_6 SSR_{,t-8,t-4} + \beta_7 Down_t + \varepsilon_{i,t-3,t-1} \quad (2)$$

$$SSTO_{i,\ t-3,t-1} = \beta_0 + \beta_1 size_{i,t} + \beta_2 ret_{i,t-3t-1} + \beta_3 vto_{i,t-3,t-1} + \beta_4 p\_volt_{i,t-3,t-1} + \beta_5 r\_volt_{i,t-3,t-1} + \beta_6 SSTO_{i,t-8,t-4} + \beta_7 Down_t + \varepsilon_{i,t-3,t-1} \quad (3)$$

The independent variables include contemporaneous share turnover ($turn_{i,t-3,t-1}$), return volatility ($r\_volt_{i,t-3,t-1}$), and price volatility ($p\_volt_{i,t-3,t-1}$). We also include a lagged dependent variable to control for serial correlation ($Sh\_sell_{,t-8,t-4}$) and the contemporaneous market-adjusted return ($ret_{i,t-3,t-1}$). The variable of interest is $Down_t$, which is an indicator variable equal to one on the IFSR downgrade announcement day. A Hausman test reveals fixed effects by stock and days. P-values are reported in parentheses.

	$Ssr_{i,\ t-3\ t-1}$	$Ssto_{i,\ t-3\ t-1}$
	[1]	[2]
intercept	4.2999***	2.8104***
	(0.000)	(0.000)
$Size_i$	-0.2425***	-0.1948***
	(0.000)	(0.000)
$ret_{i,\ t-3,\ t-1}$	14.6315***	11.4321***
	(0.000)	(0.000)
$vto_{i,\ t-3,\ t-1}$	3.7417**	102.2437***
	(0.015)	(0.000)
$pvolt_{i,\ t-3,\ t-1}$	4.7223***	6.6750***
	(0.000)	(0.000)
$rvolt_{i,\ t-3,\ t-1}$	-1.3174	-8.347***
	(0.065)	(0.000)
$Ssto_{i,\ t-8,\ t-4}$		0.3336***
		(0.000)
$Ssr_{i,\ t-8\ t-4}$	0.5662***	
	(0.000)	
$Down_t$	0.2656**	0.2205**
	(0.016)	(0.019)
Adj R^2	0.3991	0.5469
Stock FE	Yes	Yes
Day FE	Yes	Yes
Observations	12,575	12,575
Firms	25	25

Table 5
Summary Statistics
The table shows summary statistics for the opaqueness measures used in the analysis.

Variable	N	Mean	Median	SD
P/C Asset Opaqueness	25	1,699,130,954	91,824,140	4,356,077,674
P/C Net Prem Written-Total	25	3,604,777,827	150,222,921	9,198,993,734
L/H Asset Opaqueness	25	5,085,692,260	26,464,093	15,746,838,769
A/H Net Prem Written	25	1,022,660,072	14,093,009	2,100,703,612
L/H Total Assets	25	24,417,980,898	725,381,191	75,898,222,993
L/H Net Prem Written-Total	25	3,182,134,848	126,287,031	81,228,534,691
Lopaque	25	74.4037	79.9105	28.3598
Aopaque	25	18.4052	17.7136	11.3456

Table 6

Panel Regression Results

The table presents the panel regression results from estimating the following equation where the dependent variable is short-selling activity from day *t-3* to *t-1*. Short selling specifications are the standardized short ratio ($Ssr_{i,\, t\text{-}3\ t\text{-}1}$) and standardized short turnover ($Ssto_{i,\, t\text{-}3\ t\text{-}1}$).

$$SSR_{i,\, t-3,t-1} = \beta_0 + \beta_1 size_{i,t} + \beta_2 ret_{i,t-3t-1} + \beta_3 vto_{i,t-3,t-1} + \beta_4 p\_volt_{i,t-3,t-1} + \beta_5 r\_volt_{i,t-3,t-1} + \beta_6 Sh\_sell_{,t-8,t-4} + \beta_7 Down_t + \beta_8 Lopaque_t + \beta_9 Aopaque_t + \beta_{10} Down_t \, x \, Lopaque_t + \beta_{11} Down_t \, x \, Aopaque_t + \varepsilon_{i,t-3,t-1} \quad (4)$$

$$SSTO_{i,\, t-3,t-1} = \beta_0 + \beta_1 size_{i,t} + \beta_2 ret_{i,t-3t-1} + \beta_3 vto_{i,t-3,t-1} + \beta_4 p\_volt_{i,t-3,t-1} + \beta_5 r\_volt_{i,t-3,t-1} + \beta_6 Sh\_sell_{,t-8,t-4} + \beta_7 Down_t + \beta_8 Lopaque_t + \beta_9 Aopaque_t + \beta_{10} Down_t \, x \, Lopaque_t + \beta_{11} Down_t \, x \, Aopaque_t + \varepsilon_{i,t-3,t-1} \quad (5)$$

The independent variables include contemporaneous share turnover ($turn_{i,t-3,t-1}$), return volatility ($r\_volt_{i,t-3,t-1}$), and price volatility ($p\_volt_{i,t-3,t-1}$). We also include a lagged dependent variable to control for serial correlation ($Sh\_sell_{,t-8,t-4}$) and the contemporaneous market-adjusted return ($ret_{i,t-3,t-1}$). The variable of interest is $Down_t$, which is an indicator variable equal to one on the IFSR downgrade announcement day. Further the level of opaqueness in liabilities (*Lopaque*) and assets (*Aopaque*) are represented. We also interact the dummy variable and the continuous variable for opaqueness in line of business and assets ($Down_t \, x \, Lopaque_t$; $Down_t \, x \, Aopaque_t$) to determine whether the short selling is effected by the opaqueness of the insurers line of business or assets during the pre-announcement period. The variable of interest is $Down_t$, which is an indicator variable equal to one on the IFSR downgrade announcement day. A Hausman test reveals fixed effects by stock and days. P-values are reported in parentheses.

	$Ssr_{i,\, t-3\ t-1}$	$Ssto_{i,\, t-3\ t-1}$
	[1]	[2]
intercept	3.0589***	2.4502***
	(0.000)	(0.000)
$Size_i$	-0.2241***	-0.2138***
	(0.000)	(0.000)
$ret_{i,\, t-3,\, t-1}$	15.9827***	10.9415***
	(0.000)	(0.000)
$vto_{i,\, t-3,\, t-1}$	0.4964	114.6415***
	(0.994)	(0.000)
$pvolt_{i,\, t-3,\, t-1}$	5.0041***	6.3586***
	(0.000)	(0.000)
$rvolt_{i,\, t-3,\, t-1}$	-0.6105	-4.4367***
	(0.2624)	(0.000)
$Ssto_{i,\, t-8,\, t-4}$		0.3004***
		(0.000)
$Ssr_{i,\, t-8\ t-4}$	0.5394**	
	(0.000)	
$LOpaque_t$	-0.0007**	-0.0011***
	(0.047)	(0.000)
$AOpaque_t$	-0.0113***	-0.0092***
	(0.000)	(0.000)
$Down_t$	0.0546**	0.0653**
	(0.024)	(0.042)
$LOpaque_t \; X \; Down_t$	-0.0027**	-0.0069**
	(0.031)	(0.036)
$\mathrm{AOpaque}_t$ X Down_t	-0.0054**	-0.0055**
	(0.019)	(0.041)
Adj R^2	0.3993	0.5658
Stock FE	YES	YES
Day FE	YES	YES
Observations	10,958	10,958
N	25	25

Table 7
Short Selling around A.M. Best Rating Upgrades
The table shows a standard event study of market-adjusted returns and short selling around A.M. Best rating upgrades. We obtain downgrades from A.M. Best data and report the market-adjusted returns (the difference between the daily return and the CRSP equally-weighted return for a particular stock), the short ratio, and the short turnover surrounding rating downgrades. Tests for significant returns are determined by standard *t*-statistics testing for differences from zero. We test for the significance in short selling using two different methods. We also standardize short selling activity by calculating the difference between the short activity for stock *i* on day *t* and the mean short activity for stock *i* (across the sample time period). We then divide the difference by the standard deviation of daily short activity so that each short measure on each day is similarly distributed with a zero mea n and a unit variance. *T*-statistics testing whether the standardized measure is significantly different than zero (the mean) are obtain. Results from *t*-tests, which test whether the standardized and abnormal measures are significantly different than zero (the mean) are shown using asterisks.

	Adjusted Returns	Short Ratio	Std_Short Ratio	Short Turnover	Std_SShort Turnover
	[1]	[2]	[3]	[4]	[5]
t-8,t-4	0.0005	0.1856	-0.0142***	0.0013	-0.0135**
t-3	-0.0003*	0.2211	-0.0541***	0.0012	-0.0081**
t-2	0.0006	0.2301	-0.0319**	0.0016	-0.0046***
t-1	0.0035**	0.1987	-0.0628**	0.0041	-0.0265**
event day	0.0102***	0.2514	0.0823***	0.0073	0.0677***
t+1	0.0041***	0.2107	0.0471***	0.0056	0.0223**
t+2	0.0007**	0.2008	-0.0256	0.0018	-0.0183
t+3	0.0002	0.1795	-0.0498**	0.0014	-0.0147
t+4,t+8	0.0004	0.1979	-0.0227	0.0021	-0.0032

Table 8
Panel Regression Results
The table presents the panel regression results from estimating the following equation where the dependent variable is daily short-selling activity.

$$SSR_{i\,t} = \beta_0 + \beta_1 size_{i,t} + \beta_2 ret_{i,t} + \beta_3 vto_{i,t} + \beta_4 p\_volt_{i,t} + \beta_5 UP_t + \varepsilon_{i,t-5,t-1} \quad (6)$$

$$SSTO_{i\,t} = \beta_0 + \beta_1 size_{i,t} + \beta_2 ret_{i,t} + \beta_3 vto_{i,t} + \beta_4 p\_volt_{i,t} + \beta_5 UP_t + \varepsilon_{i,t-5,t-1} \quad (7)$$

The independent variables include the daily share turnover (*turn*), price volatility (*p_volt*), and market capitalization (*size*). We also include the contemporaneous returns (ret_t) and a dummy variable (*UP),* which is equal to unity if day *t* is a upgrade rating day, zero otherwise. A Hausman test reveals observed differences across stocks and days so we report two-way fixed effects estimates. *P*-values are reported in parentheses.

	$Ssr_{i,t}$	$Ssto_{i,t}$
	[1]	[2]
intercept	2.0162***	1.9512***
	(0.000)	(0.000)
$Size_i$	-0.3017	-0.1655
	(0.106)	(0.078)
$vto_{i,t}$	2.451***	99.6623***
	(0.000)	(0.000)
$pvolt_{i,t}$	2.868***	5.4438***
	(0.000)	(0.000)
$rvolt_{i,t}$	-2.2144***	-4.6621***
	(0.000)	(0.000)
$ret_{i,t}$	6.7792***	10.6291***
	(0.000)	(0.000)
Up_t	0.3797**	0.1986**
	(0.018)	(0.032)
Adj R^2	0.3396	0.4487
Stock FE	Yes	Yes
Day FE	Yes	Yes
Observations	7,042	7,042
Firms	14	14

ESSAY 3:
DOES ENTERPRISE RISK MANAGEMENT INCREASE TRANSPARENCY?

CHAPTER 3.1

INTRODUCTION

In the last few decades corporate risk management has developed from a narrowly-focused function into an enterprise-wide approach. The advent of Enterprise Risk Management (ERM) has motivated a growing body of research related to its determinants, leadership, and value-relevance (e.g. Liebenberg and Hoyt, 2003, Pagach and Warr, 2008, McShane, Nair, and Rustambekov, 2011, Hoyt and Liebenberg, 2011). While several recent studies test *whether* ERM benefits firms, there is an absence of studies that examine *how* ERM can generate value. Our paper provides some initial evidence on one potential source of value from an ERM program – an increase in transparency regarding the firm's risk profile.

Proponents of ERM argue that for firms that are highly financially and operationally complex, individuals outside the firm are likely to have difficulty in assessing the firm's financial strength and risk profile (Muelbroek, 2002). An ERM structure may enable opaque firms to provide information to outsiders (e.g. investors, regulators, and rating agencies) about their risk profile and may also serve as a signal of their commitment to risk management (Liebenberg and Hoyt, 2003). Industry commentators argue that ERM provides an opportunity to employ risk management practices to further increase management transparency, encourage consistency in aligning risk tolerance with risk appetite, and improve visibility and transparency to stakeholders.[8] Moreover, with an effective ERM program in place, and with transparency into

[8] See for example discussions at http://www.boardmember.com/Article_Details.aspx?id=2252, and http://www.ey.com/GL/en/Industries/Financial-Services/Insurance/2010-property_casualty-risk-management-governance-transparency.

that program, stakeholders have a higher comfort level in the ability of management to define and achieve value-producing objectives.[9]

Economic theory indicates several reasons why an increase in transparency, which is defined as the availability of firm-specific information to outsiders, should impact firm value (Wang, 2010). First, by reducing uncertainty and increasing transparency about a firm's performance, there would be reduction stock price volatility (Lang and Lundholm, 1996). In addition, market microstructure models predict that by increasing information and transparency there is a resulting reduction in information asymmetries in the market (Diamond and Verrecchia 1991). Meulbroek (2002) suggests that integrated risk management can facilitate performance evaluations by outsiders by making disclosures of the risk management process more informative or accessible[10] Taken together, these findings would suggest that transparency may enhance an outsider's view of a firm's risk profile resulting in value enhancement.

We test for changes in transparency around the announcement of an ERM initiative. Consistent with prior literature we use the degree of dispersion in analyst earnings forecasts as a proxy for transparency and the announcement of the appointment of a Chief Risk Officer (CRO) or Vice-President of Enterprise Risk Management (VP-ERM) as a proxy for an ERM initiative. From here forward we refer to the dispersion in analyst earnings forecasts as DISP, and the appointment of a CRO or VP-ERM as an ERM announcement. We find evidence of a significant reduction in DISP following the ERM announcement. Thus, our results suggest that ERM does increase transparency, which in turn is consistent with enhanced firm value. We extend our analysis and examine whether the increase in transparency varies according to the degree of firm

[9] http://www.theiia.org/blogs/marks/index.cfm/post/S&P%20Publishes%20Status%20Report%20on%20ERM%20

[10] McShane et al. (2011) indicates that transparency in the manner an organization's risk management philosophy is communicated to the company is a contributing factor in the S&P ERM rating process.

opaqueness. Our results indicate that the increase in transparency resulting from the adoption of an ERM program is greatest for financial firms that tend to be operationally and financially opaque.

The next section reviews the prior literature and develops our hypothesis. The sample and data are introduced in the subsequent section. The next two sections present our empirical methodology and discuss our results. The final section concludes.

CHAPTER 3.2

PRIOR LITERATURE

While there has been recent attention paid to ERM programs in the literature, by both academics and practitioners, there have been mixed results as to the value created by ERM. Hoyt and Liebenberg (2011) find a positive relation between the announcement of the appointment of a Chief Risk Officer (CRO) and firm value, while Beasley et al. (2008) find firm-specific benefits of ERM for non-financial firms. However, recently, McShane et al. (2011) show that firm value increases as firms implement increasingly more sophisticated traditional risk management methods not ERM, while Pagach and Warr (2010) investigate a firms' long-term performance around an ERM adoption and report results that ERM is not value creating.

For some firms, ERM is clearly beneficial, whereas for others the benefit may not outweigh the costs, at least as perceived by stock market investors (Meulbroek, 2002). The value provided from ERM programs arises out of the improved information related to the firm's risk profile. In firms that are highly financially and operationally complex, individuals outside the firm are likely to have difficulty in assessing the firm's financial strength and risk profile. An ERM program enables firms to better provide information to outsiders about their risk profile and also serves as a signal of their commitment to risk management (Hoyt and Liebenberg, 2011; Pagach & Warr, 2009; Beasley et al., 2008; Liebenberg & Hoyt, 2003). This increase in transparency regarding the firm's risk profile is a potential source of firm value; accordingly we focus our study on the effect of an ERM announcement on transparency. Accordingly, using an

ERM announcement and motivated by previous literature which shows increases in transparency to be value enhancing for a firm, we propose the following hypothesis.

*Hypothesis 1***:** The announcement of a CRO or VP-ERM will increase transparency.

Research has suggested that transparency may increase the accuracy of publicly available information about management's operating decisions (Francis and Martin, 2010). Additionally, transparency resulting from financial analyst following, factors into monitoring managerial behavior (Lang, Lins, and Miller, 2004). Thus, transparency may reduce the risk premium associated with the potential expropriation of shareholder wealth by opportunistic managers (Bushman, Piotroski, and Smith, 2004). Further, prior literature suggests that financial analysts also serve as external monitors of corporate managers (Jensen and Meckling, 1976). Consistent with this notion, Lang et al. (2004) find that increased analyst coverage is associated with higher firm value. However, the economic impact of transparency is not limited to these more general capital market consequences; transparency can also directly contribute to economic performance by disciplining corporate insiders in better selection of investments, more efficient risk management, and reduced expropriation of minority shareholders' wealth (Bushman and Smith, 2001).

Investigating risk management activities in the gold mining industry, Tufano (1996) suggests that transparent firms should have higher value because of lower liquidity premiums and lower discounts demanded by incompletely diversified investors and transparent firms receive greater attention from investors and analysts. Additionally, transparency reduces the likelihood of distorted investment and financing decisions that arise when managers pursue their own objectives (Morck, Shleifer and Vishny, 1990) or favor shareholders at the expense of bondholders (Myers and Majluf, 1984). Lower information asymmetry is valuable because transparency should lower adverse selection costs associated with securities issuance described in (Myers and Majluf, 1984). Collectively, this stream of literature shows that transparency can enhance shareholder wealth.

CHAPTER 3.3

SAMPLE AND DATA

Our sample consists of 100 individual firms, with a total of 128 announcements[11] of the appointment of a Chief Risk Officer (CRO) or Vice President of Enterprise Risk Management (VP-ERM) between 1993 and 2007 (Table 1). We use the announcement of the appointment of a CRO or VP-ERM as a proxy for the implementation of an ERM initiative (Hoyt & Liebenberg, 2011; Pagach and Warr, 2009; Beasley et al. 2008). Our sample determination follows Hoyt & Liebenberg (2008) and Pagach and Warr (2009), in determining firms who have announced a CRO or VP-ERM. We use Factiva, Thomson, and other search engines to perform separate keyword searches. Our search strings included the following phrases, their acronyms, as well as the individual words within the same paragraph; “chief risk officer”, “vice president of Enterprise Risk Management”, “enterprise risk management”, “integrated risk management”. We chose these particular search strings because the titles of the positions (i.e. CRO, VP-ERM) are synonymous with management of an ERM program, and the other phrases are synonymous with enterprise risk management (Liebenberg & Hoyt, 2003) (See Appendix 1).

We obtain market data from CRSP and annual accounting data from COMPUSTAT. The Firstcall summary database was used to gather the earnings forecast data. Individual firms were dropped from the sample if Firstcall data was not available for the firm around the announcement date. The Firstcall data contains median analyst earnings forecasts, the forecast standard deviation, and the number of analysts covering a specific firm. Our empirical analysis tests the

[11] In the case of multiple ERM announcements for the same firm in our sample period, we use the most recent announcement.

effect of ERM program adoption on transparency. The following section documents the variables used in our analysis.

Dependent Variable

DISP: Dispersion is computed (Eq 1) as the absolute value of the standard deviation of all individual annual earnings forecasts divided by the mean individual forecast (Barron, Stanford and Yu, 2005). A firm must have at least two individual forecasts for this measure to be computed. In our univariate analysis we partition DISP according to the closest, second closest, and third closets to the ERM announcement. The closest represents the DISP in the year immediately preceding and year immediately following the ERM announcement. The second and third closest represents the DISP in the second and third subsequent years immediately preceding and the second and third subsequent years immediately following the ERM announcement.

$$DISP_{it} = \frac{|\sigma(Annual\ EPS_{it})|}{\overline{Annual\ EPS_{it}}} \qquad (1)$$

Analysts' forecasts or recommendations have been shown to be informative and often used empirically to proxy for information quality, investor beliefs, expected growth rates, and disagreement in opinion (Ang and Ciccone, 2001). DISP is thought of as a risk measure associated with investor uncertainty (Givoly and Lakonishok, 1998). The term transparency is used to convey an interpretation that firms with lower DISP are more easily understood financially or are more transparent to investors. Accordingly, a firm is called transparent if it has low DISP.

Independent Variables

ERM: A dummy variable equal to 1 for the years following an ERM announcement and 0 for the years prior to an ERM announcement. Observations relating to the year of the ERM announcements are removed to avoid potential bias caused by the fact that these announcements happen at various times throughout the year. We hypothesize a negative relation between ERM and DISP. The average level of disagreement among analysts is expected to be lower for firms that have appointed senior officers to lead their ERM programs and communicate the firm risk profile to outsiders.

RVOLT: Stock return volatility is calculated as the standard deviation of daily stock returns for each calendar year. Alford and Berger (1999) and Thomas (2002) suggests that as volatility increases, the amount of price-relevant information that analysts must process also goes up and analysts' ability to forecast earnings declines. Thus, firms with higher volatility are expected to have greater analyst disagreement.

R&D: Research and development is the ratio of R&D expense to sales and INTA is the ratio of intangible assets to total assets. Barth et al. (1998) suggests that the level of analyst effort and possibly the quality of analysts' forecasts vary with the degree to which firm value is comprised of tangible assets.

MB: Market to Book ratio is defined as the ratio of the firm's market value (market value of equity plus the book value of total assets minus the book value of equity) to the firm's book value of total assets. Thomas (2002) includes MB as a proxy for the quality of investment opportunities.

MVE: We take the natural log of market value of equity, which is a common proxy for firm size (Thomas, 2002).

LEVG: Leverage is the ratio of long-term debt and debt in current liabilities to total assets, representing a proxy for risk. Thomas (2002) suggests that leverage adds to the volatility of earnings, and firms with higher leverage might be expected to increase dispersion among forecasts.

FIN: A dummy variable equal to 1 for financial institution (N=52) and 0 for non-financial institutions (N=48). Financial institutions are defined as firms that fall within the SIC code 6021-6282 (banking) and 6311-6411 (insurance). There is consensus in the literature that financial institutions present an increased degree of information asymmetry between shareholders/claimholders, investors and the firm due to opaqueness of their liability and asset structure (Ross, 1989; Polonchek and Miller, 1999; Babbel and Merrill, 2005; Baranoff and Sager, 2002; Zhang et al. 2009). We expect that increase in transparency resulting from the adoption of an ERM program will be greatest for financial firms that tend to be operationally and financially opaque.

Descriptive statistics and definitions for each of these variables are reported in Table 2. A few items are noteworthy. While, it is apparent that DISP is heavily skewed as its mean is almost three times greater than its median; this result is consistent with others who show dispersion extremely positively skewed and that the mean of dispersion is nearly four times larger than its median (Qu, Starks and Yan, 2004). In our multivariate analysis we trim DISP at the 5th and 95th percentiles to eliminate outliers that were observed in diagnostic tests and to correct for this skewness. CROs or VP-ERMs are in place (so ERM=1) in over one-third of sample firm-years. R&D is missing for the majority of firm-years and is accordingly eliminated from our multivariate analysis.

CHAPTER 3.4

EMPIRICAL METHODOLOGY

Our empirical analysis investigates whether DISP is lower in the years following ERM-related appointments, than before the ERM-related appointments. In our univariate test, we calculate dispersion for the three closest groups of earnings forecast estimates: closest, second closest, and third closest around (prior to and following) an announcement. The difference in DISP was calculated as the DISP before the announcement minus the DISP following an announcement. We hypothesize that if DISP following an ERM announcement is less than prior to the announcement there is an indication of increased transparency as a result of the announcement. We perform a simple univariate comparison (*t*-test) to determine significance of the difference in DISP if any exists.

Our multivariate analysis examines the relation between ERM and DISP while controlling for other DISP determinants. OLS1 is an ordinary least squares regression, OLS2 adds year dummies to OLS1, and the third model is a fixed effects regression that includes both firm and year effects (dummies). The fixed effects model is preferred over a random-effects model as determined by our Hausman specification test (Hausman Chi-squared=30.67). Specifically, we model DISP as a function of whether an ERM program was in place and a set of DISP determinants. If an ERM announcement provides transparency (i.e. reduction in DISP) into a firms risk profile, then we expect the estimate for *ERM* to be significantly negative. Specifically, the following equation is estimated across all firms (i=1 to 100) that announced an ERM initiative during the sample period (t=1990 to 2006).

$$DISP_{it}= \beta_0 + \beta_1 ERM_{it}+ \beta_2 RVOLT_{it}+ \beta_3 INTA_{it}+ \beta_4 MB_{it}+ \beta_5 MVE_{it}+ \beta_6 LEVG_{it}+ \varepsilon_{it} \quad (2)$$

We extend our analysis of DISP around ERM announcements and test the relation between changes in DISP around ERM announcements for financial institutions. Specifically, this test is to determine whether changes in DISP resulting from the announcements differs for firms that are operationally and financially opaque. Estimation results for the following equation are reported in Table 7.

$$DISP_{i,t}= \beta_0 + \beta_1 ERM_{i,t}+ \beta_2 RVOLT_{i,t}+ \beta_3 INTA_{i,t}+ \beta_4 MB_{i,t}+ \beta_5 MVE_{i,t}+ \beta_6 LEVG_{i,t}$$
$$+ \beta_7 FIN_{i,t}+ \beta_8 FIN \text{ X } ERM_{i,t} + \varepsilon_{it} \quad (3)$$

The dependent and independent variables are the same as those defined in equation (1) with the exception of FIN and its interaction with ERM. As in equation 2, we expect the estimate for *ERM* to be significantly negative. Further, due to the opaque and operationally complex nature of financial instructions, we expect the estimate for FIN to be significantly positive. Lastly, we interact ERM and FIN to determine whether the effect of ERM on DISP differs for financial firms. As before, OLS1 as an ordinary least squares regression, OLS2 adds year dummies to OLS1, and the third model is a fixed effects regression.

CHAPTER 3.5

RESULTS

Table 3 report the univariate findings for annual dispersion in analysts' earnings forecast for the average of each of the three closest groups of estimates. The findings suggest that around a CRO or VP-ERM announcement there is a significant decrease in dispersion following such an announcement. Table 4 presents the correlation coefficients for each of the variables.

Table 5 reports differences in means and medians between firm-years where a CRO or VP-ERM is in place and those where the appointment has not yet been made. Most notably, the mean and median DISP is significantly lower in firm-years where an ERM initiative is in place. Table 6 reports the results for ERM across all three models which confirm the univariate results discussed above. The announcement of an ERM initiative results in a significant reduction in uncertainty regarding future earnings, as proxied by DISP.

We extend our analysis and examine whether the increase in transparency varies according to the degree of firm opaqueness. Our results indicate that the increase in transparency resulting from the adoption of an ERM program is greatest for financial firms that tend to be operationally and financially opaque. In table 7, columns [1 & 2], we find a positive and significant FIN coefficient and an increasingly negative and significant ERM coefficient. The positive and significant FIN coefficient indicates that DISP is higher in financial firms compared to non-financial firms. This result would be expected as financial firms are arguably more opaque than non-financial firms (Ross, 1989; Polonchek and Miller, 1999; Babbel and Merrill, 2005; Baranoff and Sager, 2002; Zhang et al. 2009). Taken together, the indication is ERM announcements within financial firms have a stronger influence on an increase in transparency than that of non-financial firms. This result would be consistent with the intuition that ERM provides an increase in the transparency of normally more opaque firms. We interact *FIN with ERM* to determine whether the effect of ERM on DISP differs for financial firms. The results shows the *FIN X ERM* coefficient is negative and significant suggesting that the reduction in DISP is greater for financial firms than for less opaque non-financial firms These results are confirmed in columns [3 & 4] of the fixed effects model when comparing the negative and significant ERM coefficient between the sample of financial and non-financial firms (-0.0493 to -0.0411). This result shows the increase in transparency around an ERM announcement is more pronounced for financial firms than for non-financials.

CHAPTER 3.6

CONCLUSIONS

The emergence of ERM has led to an increasing body of literature investigating its determinants, management structure, and value-relevance (e.g. Liebenberg and Hoyt, 2003, Pagach and Warr, 2008, McShane, Nair, and Rustambekov, 2011, Hoyt and Liebenberg, 2011). While several recent studies test *whether* ERM benefits firms, there is an absence of studies that examine *how* ERM can generate value. Our paper provides some initial evidence on one potential source of value from an ERM program; an increase in transparency regarding the firm's risk profile. Finance theory suggests several ways in which transparency creates value for shareholders, such as information accuracy, reduced risk premium, and reduced uncertainty in corporate investment and operating activities.

Using a sample of 100 firms that announced ERM-related appointments between 1993 and 2007, we examine DISP surrounding these ERM announcements. Our empirical analysis investigates whether DISP is lower in the years following ERM-related appointments, than before the ERM-related appointments. Specifically, we model DISP as a function of whether an ERM program was in place and a set of DISP determinants. We find that transparency increases after ERM-related announcements. Our results also indicate that the increase in transparency resulting from the adoption of an ERM program is greatest for financial firms that tend to be operationally and financially opaque.

Table 1. The table presents the distribution of CRO or VP-ERM announcements over the period 1993-2007.

	Total	**Total-CRO**	**Total-VPERM**	**Sample**	**Sample-CRO**	**Sample-VPERM**
Years						
1993	1	1	0	0	0	0
1994	5	2	3	2	0	1
1995	8	4	4	5	3	2
1996	6	4	2	2	2	0
1997	8	4	2	2	2	1
1998	5	4	1	2	1	1
1999	14	5	9	4	1	5
2000	21	13	6	8	5	2
2001	14	8	6	8	6	4
2002	20	9	6	14	6	7
2003	25	12	13	18	11	6
2004	31	19	12	23	14	8
2005	29	14	15	18	11	7
2006	10	5	5	8	4	4
2007	17	9	8	14	6	8
Total	***214***	***113***	***92***	***128***	***72***	***56***

Table 2. The table presents descriptive statistics and definitions for each of the variables.

Variable	*Definition*	*N*	*Mean*	*Median*
DISP	Average analyst dispersion following an ERM announcement	907	0.1028	0.0386
ERM	Equal to 1 the years following an ERM announcement, 0 otherwise	907	0.3451	0.0000
LEVG	Ratio of long-term debt and debt in current liabilities to total assets	651	0.2131	0.2527
MB	Ratio of the firm's market value to the firm's book value of total assets	907	1.1369	1.0883
R&D	Ratio of R&D expense to sales	146	0.0264	0.0159
INTA	Ratio of intangible assets to total assets	809	0.0672	0.0210
MVE	Natural log of the Market value of equity (000s)	907	4.2046	3.7325
RVOLT	Annual return volatility	761	0.0201	0.0197

Table 3.
The table presents statistics that describe the dispersion in analysts' *Annual* earnings estimates around the announcement of a Chief Risk Officer (CRO) or a Vice President of Enterprise Risk Management (VP-ERM). Dispersion is calculated as the absolute value of the standard deviation of the analysts forecast divided by the mean forecast [abs (SD/Mean)]. Three dispersion time points relative to the announcement date (closest, second closest, and third closest) were calculated to examine dispersion prior to and following the announcement. Panel A reports the summary statistics and a univariate (t-test) comparison of the three time points and the difference of mean dispersion prior to and following an announcement. Panels B, & C report statistics and differences for the average of the next closest dispersion measures, and the average of the third closest dispersion measures, around the announcement date respectively.

Panel A. Annual Dispersion: Average of the Closest Estimates to the Announcement					
	N	Mean	Std	Minimum	Maximum
Before	103	.1416	.2056	0.0000	1.5143
After	106	.0824	.1262	0.0000	.9427
Difference	102	.0593***	.1912	-.501	1.4102
Panel B. Annual Dispersion: Average of the Second Closest Estimates to the Announcement					
	N	Mean	Std	Minimum	Maximum
Before	103	.1745	.3269	0.0000	2.9316
After	106	.0762	.0972	0.0000	0.5874
Difference	102	.0983***	.3019	-.167	2.8418
Panel C. Annual Dispersion: Average of the Third Closest Estimates to the Announcement					
	N	Mean	Std	Minimum	Maximum
Before	103	.1774	.2885	.0118	2.0442
After	106	.0718	.088	.0053	0.5496
Difference	102	.1059***	.2527	-.098	1.9553

***, **,* Statistically significant at the 0.01, 0.05, and 0.10 levels, respectively.

Table 4. The table presents correlation statistics between each of the variables.

Variables	*DISP*	*ERM*	*LEVG*	*MB*	*R&D*	*INTA*	*MVE*	*RVOLT*
DISP	-							
ERM	-0.06389**	-						
LEVG	0.1162**	-0.0127	-					
MB	0.00381	0.01526	-0.0682*	-				
R&D	0.16778**	-0.04206	-0.37847***	0.62***	-			
INTA	0.03761	0.12027**	0.24528***	0.21783***	-0.20408**	-		
MVE	-0.04182	0.19774***	-0.01434	0.08898**	0.01901	-0.02547	-	
RVOLT	0.03036	0.03751	0.04436	0.06332*	-0.18894**	0.21521***	-0.04904	-

***,**,* represent statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 5. The table presents differences in means and medians between firm-years where a CRO or VP-ERM is in place and those where the appointment has not yet been made.

	ERM=1			ERM=0				
Variable	*N*	*Mean*	*Median*	*N*	*Mean*	*Median*	Δ *Mean*	Δ *Median*
DISP	313	0.1841	0.0750	594	0.3795	0.1459	-0.1954**	-0.0708808***
LEVG	258	0.2825	0.2873	393	0.2875	0.3039	-0.0050	-0.0165
MB	313	1.3774	1.2269	594	1.3567	1.1492	0.0208	0.077***
R&D	85	0.0258	0.0154	61	0.0295	0.0157	-0.0037	-0.0003
INTA	303	0.0894	0.0468	506	0.0604	0.0081	0.0289***	0.0387***
MVE	313	4.4489	3.8357	594	3.9843	3.6172	0.4646***	0.2185***
RVOLT	309	0.0183	0.0157	452	0.0176	0.0159	0.0007	-0.0002

***,**,* represent statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 6.
Panel Regression Results
The table presents the panel regression results from estimating the following equation.

$DISP_{i,t} = \beta_0 + \beta_1 ERM_{i,t} + \beta_2 RVOLT_{i,t} + \beta_3 INTA_{i,t} + \beta_4 MB_{i,t} + \beta_5 MVE_{i,t} + \beta_6 LEVG_{i,t} + \varepsilon_{it}$ (1)

The dependent variable *DISP* is the absolute value of the standard deviation of all individual analyst earnings forecasts (annually) divided by the mean individual forecast. Our variable of interest is *ERM*, which is a dummy variable equal to 1 for the years following a CRO or VP-ERM announcement and 0 for the years prior to an ERM announcement. Leverage (LEVG) is the ratio of long-term debt and debt in current liabilities to total assets, representing our proxy for risk. Market to book (*MB*) ratio is defined as the ratio of the firm's market value (market value of equity plus the book value of total assets minus the book value of equity) to the firm's book value of total assets. INTA is the ratio of intangible assets to total assets. Market value of equity (*MVE*) is our proxy for firm size. Stock return volatility (*RVOLT*) is calculated as the standard deviation of daily stock returns for each calendar year. P-values are reported in parentheses. ***,**,* indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.

	OLS1	*OLS2*	*Fixed Effects*
ERM	-0.0553385***	-0.0604969**	-0.0453204*
	(0.015)	(0.024)	(0.027)
LEVG	0.1972933***	0.1848344***	0.2809068**
	(0.047)	(0.047)	(0.114)
MB	-0.031851***	-0.0379054***	-0.0922466***
	(0.014)	(0.014)	(0.022)
INTA	0.075	0.103	0.3549053**
	(0.063)	(0.064)	(0.159)
MVE	-0.0034**	-0.0061**	-0.0048**
	(0.000)	(0.000)	(0.000)
RVOLT	3.142765**	5.323854***	2.891571**
	(0.797)	(0.972)	(1.145)
Constant	0.1479298***	0.1441625***	0.1503168***
	(0.030)	(0.041)	(0.058)
Year Effects	No	Yes	Yes
Firm Effects	No	No	Yes
Hausman Chi-sq.			30.67*
# observations	497	497	497
R-squared	0.122	0.157	0.206

Table 7.
Panel Regression Results
The table presents the panel regression results from estimating the following equation.

$DISP_{i,t} = \beta_0 + \beta_1 ERM_{i,t} + \beta_2 RVOLT_{i,t} + \beta_3 INTA_{i,t} + \beta_4 MB_{i,t} + \beta_5 MVE_{i,t} + \beta_6 LEVG_{i,t} + \beta_7 FIN_{i,t} + \beta_8 FIN \text{ X } ERM_{i,t} + \varepsilon_{it}$
(2)

The dependent variable *DISP* is the absolute value of the standard deviation of all individual analyst earnings forecasts (annually) divided by the mean individual forecast. Our variable of interest is *ERM*, which is a dummy variable equal to 1 for the years following a CRO or VP-ERM announcement and 0 for the years prior to an ERM announcement, and FIN which is a dummy variable equal to 1 for financial institution (N=52) and 0 for non-financial institutions (N=48). We also interact the dummy variables (ERM X FIN) to determine whether the effect of ERM on DISP differs for financial firms. Leverage (LEVG) is the ratio of long-term debt and debt in current liabilities to total assets, representing our proxy for risk. Market to book (*MB*) ratio is defined as the ratio of the firm's market value (market value of equity plus the book value of total assets minus the book value of equity) to the firm's book value of total assets. INTA is the ratio of intangible assets to total assets. Market value of equity (*MVE*) is our proxy for firm size. Stock return volatility (*RVOLT*) is calculated as the standard deviation of daily stock returns for each calendar year. P-values are reported in parentheses. ***,**,* indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.

	OLS1	*OLS2*	*Fixed Effects*	
			Financial Institution	*Non-Financial Institution*
Constant	0.1517**	0.1438**	0.1619**	0.1622**
	(0.023)	(0.017)	(0.018)	(0.024)
ERM	-0.0598**	-0.0647**	-0.0493**	-0.0411**
	(0.019)	(0.024)	(0.027)	(0.042)
LEVG	0.1987**	0.1883**	0.2976**	0.3103**
	(0.041)	(0.027)	(0.021)	(0.045)
MB	-0.0412**	-0.0367**	-0.0798**	-0. 0614**
	(0.047)	(0.016)	(0.022)	(0.018)
INTA	0.0543	0.0867	0.4128**	0.4015**
	(0.126)	(0.141)	(0.046)	(0.049)
MVE	-0.0021**	-0.0016**	-0.0028**	-0.0034**
	(0.013)	(0.016)	(0.027)	(0.014)
RVOLT	2.2351**	5.1166**	3.0012**	2.9778**
	(0.038)	(0.047)	(0.028)	(0.025)
FIN	0.0775**	0.0813**		
	(0.026)	(0.014)		
FIN X ERM	-0.0988**	-0.0837**		
	(0.031)	(0.041)		
Year Effects	No	Yes	Yes	Yes
Firm Effects	No	No	Yes	Yes
# observations	497	497	203	294
R-squared	0.117	0.186	0.234	0.216

BIBLIOGRAPHY

BIBLIOGRAPHY

Alford, A., Berger, P. (1999). A Simultaneous Equations Analysis of Forecast Accuracy Analyst Following, and Trading Volume. *Journal of Accounting, Auditing, and Finance* 14, 219–240.

Aitken, M., Frino, A., McCorry, M., Swan, P., (1998). Short sales are almost instantaneously bad news: Evidence from the Australian stock exchange. *Journal of Finance* 53, 2205-2223.

Ang, J., and Ciccone, S. (2000), International Differences in Financial Transparency, Working Paper, University of New Hampshire.

Arnold, T., Butler, A., Crack, T., Zhang, Y., (2005). The information content of short interest: A natural experiment. *Journal of Business* 78, 1307-1335.

Avramov, D., Chordia, T., Goyal, A., (2006). The impact of trades on daily volatility. *Review of Financial Studies* 19, 1241-1278.

Babbel, D., and Merrill, C., (2005). Real and Illusory Value Creation by Insurance Companies. *Journal of Risk and Insurance* 72, 1-21.

Baranoff, E., and Sager, T., (2002). The Relationship Between Asset risk, Product Risk, and Capital in the Life Insurance Industry. *Journal of Banking and Finance* 26, 1181-1197.

Barron, O., and Stuerke, P. (1998). Dispersion in Analysts' Earnings Forecasts as a Measure of Uncertainty. *Journal of Accounting, Auditing, and Finance,* 13, 243–268.

Barth, M., Kasznik, R., and McNichols, M. (1998). Analyst Coverage and Intangible Assets. Unpublished Working Paper, Stanford University, Stanford, CA.

Beasley, M., Pagach, D., and Richard, W. (2008), The Information Conveyed in Hiring Announcements of Senior Executives Overseeing Enterprise-Wide Risk Management Processes. *Journal of Accounting, Auditing and Finance* 23, 311-332.

Blau, B., (2010). Autocorrelation in daily short-sale volume. Working paper. Utah State University – Jon M. Huntsman School of Business.

Blau, B., Pinegar, J., (2010). Earnings announcements, price convexity, and short selling profits. Working paper. Utah State University – Jon M. Huntsman School of Business.

Blau, B., Wade, C., (2011). Informed or speculative: Short selling analyst recommendations. Journal of Banking and Finance. Forthcoming.

Boehmer, E., Jones, C., Zhang, X., (2008). Which shorts are informed? *Journal of Finance* 63, 491-527.

Bushman, N., and Smith, A. (2001). Financial Accounting Information and Corporate Governance. *Journal of Accounting and Economics* 32, 237-333.

Bushman, N., Piotroski, J., and Smith, A. (2004). What Determines Corporate Transparency? *Journal of Accounting Research* 42, 207-252.

Butler, R. J. (1994). The Economic Determinants of Workers Compensation Trends. *Journal of Risk & Insurance*, *6*, 1-19.

Butler, R. J. 1996. Lost Injury Days: Moral Hazard Differences Between Tort and Workers' Compensation, *Journal of Risk & Insurance, 63,* 405-433.

Butler, R. J., Baldwin, M. L., & Johnson, W. G. (2001). The Effects of Worker Heterogeneity on Duration Dependence: Low-Back Claims in Workers Compensation, The *Review of Economics and Statistics*, 83, 708-716.

Butler, R. J., Durbin, D. L., &. Helvacian, N. (1996). Increasing Claims for Soft Tissue Injury in Workers' Compensation: Cost Shifting and Moral Hazard, *Journal of Risk and Uncertainty*, 13, 73-87.

Butler, R. J., Garner, B. D., & Garner, H. H. (1997). Workers' Compensation Costs When Maximum Benefits Change, Journal of Risk and Uncertainty, 15, 259–269.

Butler, R. J., Garner, B. D., & Garner, H. H. (1998). More than Cost Shifting: Moral Hazard Lowers Productivity, *Journal of Risk & Insurance,* 65, 671-688.

Butler, R. J., &.Worrall, J. D. (1983). Workers' Compensation: Benefit and Injury Claim Rates in the Seventies. *Review of Economics and Statistics,* 65, 580-589.

Butler, R. J., &.Worrall, J. D. (1985). Work Injury Compensation and the Duration of Nonwork Spells, *Economic Journal,* 95, 714- 724.

Butler, R. J., &.Worrall, J. D. (1991). Claims Reporting and Risk Bearing Moral Hazard in Workers' Compensation, *Journal of Risk & Insurance,* 58(2), 191-204.

Chakrabarty, B., Shkilko, A., (2008). Information leakages in financial market: Evidence from shorting around insider sales. Working paper. Wilfred Laurier.

Chelius, J. R. (1977). *Workplace Safety and Health.* Washington, DC: American Enterprise Institute.

Chelius, J. R. (1982). The Influence of Workers Compensation on Safety Incentives. *Industrial and Labor Relations Review* 35(2), 235-242.

Chelius, J. R., & Kavanaugh, K. (1988). Workers' Compensation and the Level of Occupational Issues, *Journal of Risk & Insurance*, 55, 315-323.

Christophe, S., Ferri, M., Angel, J., (2004). Short selling prior to earnings announcements. *Journal of Finance* 59, 1845-1875.

Christophe, S., Ferri, M., Hsieh, J., (2010). Informed trading before analyst downgrades: Evidence from short sellers. *Journal of Financial Economics* 95, 85-106.

Colquitt, L., Hoyt, R., McCullough, K., (2006). The impact of asbestos and environmental reserves increases on shareholder wealth. *North American Actuarial Journal* 10, 17-31.

Cummins, J., Danzon, P., (1997). Price, financial quality, and capital flows in insurance markets. *Journal of Financial Intermediation* 6, 3-38.

Danzon, P. M. & Harrington, S. E. (2001). Workers' Compensation Rate Regulation: How Price Controls Insurance Costs, *Journal of Law & Economics*, 44, 1-36.

Daske, H., Richardson, A., Tuna, I., (2005). Do short sale transactions precede bad news events? Working paper. University of Pennsylvania.

Desai, H., Ramesh, K., Thiagarajan, R., Balachandran, B., (2002). An investigation of the information role of short interest in the NASDAQ market. *Journal of Finance* 52, 2263-2287.

Diamond, D., Verrecchia, R., (1987). Constraints on short selling and asset price adjustment to private information. *Journal of Financial Economics* 18, 277-312.

Diether, K., Lee, K., Werner, I., (2009). Short-sale strategies and return predictability. *Review of Financial Studies* 22, 575-607.

Diether, K., Malloy, C., and Scherbina, A. (2002). Differences of Opinion and the Cross-section of Stock Returns. *Journal of Finance* 57, 2113–2141.

Dionne, G. & St.-Michel, P. (1991). Workers' Compensation and Moral Hazard, *Review of Economics and Statistics* 73, 236-244.

Doherty, N., Phillips, R., (2002). Keeping up with the Joneses: Changing rating standards and the buildup of capital by U.S. property-liability insurers. *Journal of Financial Services Research* 21, 55.

Engelberg, J., Reed, A., Ringgenberg, M., (2010). How are shorts informed: Short sellers, news, and information processing? Working paper. University of North Carolina (UNC) at Chapel Hill - Kenan-Flagler Business School.

Fenn, P. (1981). Sickness Duration, Residual Disability, and In- come Replacement: An Empirical Analysis. *The Economic Journal*, 91, 158-173.

Flannery, M., Kwan, S., Nimalendran, M., (2004). Market evidence on the opaqueness of banking firm's assets, *Journal of Financial Economics* 71, 419-460.

Francis, J., and Martin, X. (2010). Acquisition Profitability and Timely Loss Recognition. *Journal of Accounting and Economics* 49, 161-178.

Givoly, D. and Lakonishok, J. (1984). Properties of Analysts' Forecasts of Earnings: A Review and Analysis of the Research. *Journal of Accounting Literature* 3, 117–152.

Halek, M., Eckles, D., (2010). Effects of analysts' ratings on insurer stock returns: Evidence of asymmetric responses. *Journal of Risk and Insurance* 77, 801-827.

Halek, M., Eckles, D., (2011). Determinants of abnormal reactions to ratings downgrades. Working paper. University of Wisconsin-Madison.

Hausman, J., (1978). Specification tests in econometrics. *Econometrica* 46, 1251-1271.

Hoyt, R. and Liebenberg, A. (2011). The Value of Enterprise Risk Management. *Journal of Risk and Insurance*, Forthcoming.

Irvine, P., Lipson, M., Puckett, A., 2007. Tipping. *Review of Financial Studies* 20, 741-768.

Jensen, M., and Meckling, W. (1976). Theory of the Firm: Managerial Behavior, Agency Cost and Ownership Structure. *Journal of Financial Economics* 3, 305-360.

Johnson, T. (2004). Forecast Dispersion and the Cross Section of Expected Returns. *Journal of Finance*, 5, 1957-1978.

Khan, M., Lu, H., (2008). Do short sellers front-run insider sales. Working paper. MIT Sloan School.

Koski, J., Scruggs, J., (1998). Who trades around the ex-dividend day: Evidence from NYSE audit file data? *Financial Management* 27, 58-72.

Krueger, A., and Burton, J., (1990). The Employers' Costs of Workers' Compensation Insurance: Magnitudes, Determinants, and Public Policy. *The Review of Economics and Statistics*, 72, 228-240.

Lakonishok, J., Vermaelen, T., (1986). Tax-induced trading around ex-dividend days. *Journal of Financial Economics* 3, 287-319.

Lamoureux, C., Lastrapes, W., (1990). Heteroskedasticity in stock return data: Volume versus GARCH effects. *Journal of Finance* 45, 221-229

Lang, M., and Lundholm, K. (1996). Corporate Disclosure Policy and Analyst Behavior. *The Accounting Review* 71, 467-493.

Lang, M., Lins, K., and Miller, D. (2004). Concentrated Control, Analyst Following, and Valuation: Do analysts Matter Most When Investors are Protected Least? *Journal of Accounting Research* 42, 589-623.

Liebenberg, A., and Hoyt, R. (2003). Determinants of Enterprise Risk Management: Evidence from the Appointment of Chief Risk Officers, *Risk Management and Insurance Review*, 6, 37-52.

McShane, M., Nair, A., and Rustambekov, E. (2011). Does Enterprise Risk Management Increase Firm Value? *Journal of Accounting, Auditing, and Finance.* Forthcoming.

Meulbroek, L. (2002). Integrated Risk Management for the Firm: A Senior Manager's Guide. *Journal of Applied Corporate Finance* 14, 56-70.

Meyer, B. D., Viscusi, W. K., & Durbin, D. L. (1995). Workers' Compensation and Injury Duration: Evidence from a Natural Experiment, *American Economic Review*, 85, 322-340.

Moore, M., & Viscusi, W., (1989). Promoting Safety Through Workers' Compensation: The Efficacy and Net Wage Costs of Injury Insurance, *The RAND Journal of Economics*, 20, 499-515.

Morck, R., Shleifer, A., and Vishny, R. (1990). Do Managerial Objectives Drive Bad Acquisitions. *Journal of Finance*, 1, 31-48.

Myers. S., and Majluf, N. (1984). Corporate Financing and Investment Decisions When Firms Have Information that Investors Do Not. *Journal of Financial Economics* 13, 187-221.

Nocco, B., and Stulz, R. (2006). Enterprise risk management: Theory and practice. Working Paper, *Ohio State University.*

Pagach, D., and Richard, W. (2010). The Effects of Enterprise Risk Management on Firm Performance. Working Paper, North Carolina State University**.**

Pagach, D., and Richard, W. (2011). The Characteristics of Firms that Hire Chief Risk Officers. *Journal of Risk and Insurance*, 78, 185-211.

Parekh, R., (2006). Quanta quits most lines after huge storm loss: Lower rating cripple insurer. *Business Insurance* 1, 1-12.

Phillips, R., Cummins, D., Allen, F., (1998). Financial pricing of insurance in the multiple line insurance company. *Journal of Risk and Insurance* 65, 597-636.

Polonchek, J., Miller, R., (1999). Contagion effects in the insurance industry. *Journal of Risk and Insurance* 66, 459-475.

Pottier, S., (1998). Life insurer financial stress, Best's ratings and financial ratios. *Journal of Risk and Insurance* 65, 275-288.

Pottier, S., Sommer, D., (1999). Property-liability insurer financial strength ratings: Differences across ratings agencies. *Journal of Risk and Insurance* 66, 621-642.

Qu, S, Stark, L., and Yan, H. (2004). Risk, Dispersion of Analyst Forecasts and Stock Returns, Working Paper.

Ross, S., (1989), Institutional markets, financial marketing, and financial innovation, *Journal of Finance* 44, 541-556.

Ruser, J. W. (1985). Workers' Compensation Insurance, Experience-Rating, and Occupational Injuries. *Rand Journal of Economics*, 16, 487-503.

Ruser, J. W. (1991). Workers' Compensation and Occupational Injuries and Illnesses, *Journal of Labor Economics*, 9(4), 325-350.

Ruser, J.W. (1998). Does Workers' Compensation Encourage Hard to Diagnose Injuries? *Journal of Risk & Insurance*, 65, 101-124.

Senchack, A., Starks, L., (1993). Short sale restrictions and market reaction to short-interest announcements. *Journal of Financial and Quantitative Analysis* 28, 177-194.

Schwartz, R., (1994). Good, better, best. ReActions 14, 34-35.

Sclafane, S., (2000). Insurers driven by analysts, rating agencies. National Underwriter, Property & Casualty/Risk & Benefits Management Edition 104, 7-14.

Sias, R., (2004). Institutional herding. *Review of Financial Studies* 17, 165-206.

Stulz, R. (1996). Rethinking risk management, *Journal of Applied Corporate Finance*, 9, 3-8.

Thomas, S. (2002). Firm Diversification and Asymmetric Information: Evidence from Analysts' Forecasts and Earnings Announcements. *Journal of Financial Economics* 64, 373–396.

Tufano, P., (1996). Who manages risk? An empirical examination of risk management practices in the gold mining industry. *Journal of Finance*, 51 (4), 1097-1137.

Wang, X. (2010). Tax Avoidance, Corporate Transparency, and Firm Value. Working Paper. University of Texas at Austin.

Zhang, T., Cox, L., Van Ness, R. (2006). Adverse selection and the opaqueness of insurers. *Journal of Risk and Insurance* 76, 295-321.

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